JURIHUM: Jurnal Inovasi dan Humaniora
Volume 1, No.6 April, 2024
ISSN 3025-7409 (Media Online)
Hal 879-891

Artificial Intelligence in Manufacturing and Processing: A Comprehensive Review of Applications and Future Trends

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Abstract: The renewed strength of Friday robots in the production and processing of products is happening with the assistance of Artificial Intelligence (AI), and the intelligent review becomes fiercer and more ground-breaking. This review reviews the most important concepts of AI and points out the ways it is applied to production planning and predictive maintenance, quality control, robotics, and supply chain optimization. In processing, AI is used in developing processes, monitoring in-situ and safety standards in pharmaceutical, chemical and food companies. The examples of the best companies are the real cases to prove the effectiveness of the improvement of the productivity, quality, and sustainability. Beside its capability to change the world, the implementation of AI is confronted with problems of data quality, cost of implementation, lack of skills in the labor force and ethics. The additional new trends described in the review are explaining AI, edge AI, hyper automation, and sustainable AI practices. Overall, the article notes that the journey to AI integration is not easy, yet it is the important step towards having robust, adaptive, and future-sustaining industrial systems.

Key words: Artificial Intelligence, Manufacturing, Processing Industries, Machine Learning, Predictive Maintenance, Quality Control, Automation, Edge Computing, Sustainability.

INTRODUCTION

Processing and manufacturing industry is ever known to trigger an increase in economic growth, innovation and advancement in technology. With the First Industrial Revolution, which saw the initiation of mechanization, through the Third that has led to automation, each industrial step has brought about new tools and methods of doing things that have changed the volume, the quantity and the quality of its production [1]. We are in a different revolution (fourth revolution) and Artificial Intelligence (AI) is taking shape as the basis of change in the following aspects. Artificial intelligence can be termed as the production of computer systems that can perform duty that usually require human intelligence [2].

It deals with the use of machine learning (learning), recognition of patterns (computer vision), making of decisions (expert systems) and dynamic responsive environments (reinforcement learning). AI cross-section combination with other digital technologies such as the Internet of Things (IoT), Big Data Analytics and Cyber-Physical Systems is bringing to birth smart manufacturing and smart processing systems that are adaptive, autonomously and real-time optimized [3].

The list of functions AI plays in manufacturing is very wide. It enables anticipatory maintenance of equipment’s that reduces loss of time and operating expenses. In the aspect of quality control, the AI vision systems rate highly in terms of detecting fault in products with its level of reliability being very high. Decision making Datlas-supported types better production arrangement and do this by way of anticipation and streamlining, and self-governing robots are becoming more recognizable on the assembly-line, in logistics and hazardous areas [4]. Besides being more and more successful in improving the levels of productivity, these AI integrations have shown very encouraging results in safer and more sustainable operations.

The processing industries which consist of food, chemicals, pharmaceuticals, and materials are also revolutionized by AI. It enables to control well difficult chemical processes or heat processes and improves the yield and energy consumption. The AI algorithm used through the possibilities of the real-time monitoring and the anomaly detection could be used to prevent breakages, guarantee the quality of products and safety of the most vulnerable processes. A case in point is using AI in the process of food processing to optimize the times of mixture, microbial growth, and the need of hygienic conditions. AI is also applied into the pharmaceutical sector, in the management of batch and drug formulation as well as the creation of individualized drugs [5].

Though the possibility is immense indeed, the use of AI in the manufacturing and processing does not emerge devoid of concerns. The mergers in these industries may be complex and costly at times where the infrastructure is not new. The lack of standardizations of data formats strangles the interoperability and scale, as well. Along with it, the skills gap that is common in the workforce today becomes a severe issue to the development of AI initiatives, and retraining and reskilling initiatives are necessitated [6]. The ethical aspect of data security, task displacement, and AI transparency adds even more complications to this situation. This literature review will provide the full description of the current situation, usage and problems and also future of AI in manufacturing and processing. It compiles findings of research or academy study, industry case studies, and emerging trends to offer the in-depth announcement of how AI can disrupt these key industries [7]. That way, it provides the guidelines on how AI can be used by organizations, researchers and policymakers in such a way, so that we can make sustainable industrial development.

THE INTELLIGENCE STACK: FOUNDATIONS OF AI IN INDUSTRIAL TRANSFORMATION

To understand the ground-breaking impact of artificial intelligence (AI) in production and processing, one should admire the background of concept and technique of using AI in the industry. Application of AI in an industrial environment is primarily focused upon the modeling of mental capabilities (cognition) such as learning, reasoning, perception and decision-making with the aim of optimizing complicated systems, augmenting the degree of automation and performance of processes [8].

Machine Learning (ML): ML involves patterns that learn, through the use of historic data, and are used to make predictions, or make decisions, but are not traditionally programmed. Supervised learning tends to be used to perform quality checks, category and predictive maintenance whereas unsupervised learning is used to spot anomalies or clusters of identical patterns of behaviours in a set of data [9].

Deep Learning (DL): Deep learning is a subset of ML which utilizes very deep neural networks to process large and unstructured information like pictures, videos or sensor data. It is used in visual inspection system, speech recognition and in manufacturing robotics [10].

Computer vision: This is the field of concern which is in charge of aiming the task of machines which is designed to change the visual information to the machine based decisions and meaning. In the manufacturing process, defect inspection, surface inspection monitoring are carried out during the production with the use of camera and imaging system; we are using the term manufacturing in that context [11].

Natural Language Processing (NLP): NLP is not applied so much in the core of the processing but it is fantastic in terms of connecting the AI system and the human staff. It has been used in chatbots, voice-control interfaces as well as being used in the workplace in the processing of technical texts [12].

Reinforcement Learning (RL): RL are made up of agents whose aim is to learn the actions to perform in an environment so as to maximize on rewards through learning; in this case cumulative rewards. Even more broadly has been its application to process control, adaptive scheduling and to robotics where a system requires learning about what actions to take best in an interaction model [13].

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Internet of Things (IoT): the sensors of the Internet of Things will generate a huge volume of real-time data about machines, equipment and processes. AI algorithms utilise this data to optimise the operations, fails detection, predictive analysis [14].

Big Data Analytics: The industrial environments produce data of a high volume and high frequency sources. The concept behind the Big Data platforms is to supply the requirements of the systems of the AI to store and analyze this data so as to create usable information [15].

Digital Twins: Digital twin is a computer based model of a physical system or process. With the use of AI models, digital twins simulate operations, anticipate failures before they occur, and conduct tests, allowing improvement of the processes without affecting the actual production [16].

Cyber-Physical Systems (CPS): They are compositions of computations, networks and physical processes. The thing is that AI is the lifeblood of CPS that allows smart factories and processing plants to measure and control real-time processes independently. In combinations with contemporary industrial forms, such AI technologies make it possible to provide smart, adaptive, and self-governing systems [17]. Learn about something new relying on the information they process and improve over time Take smarter decisions without involving humans and contribute to their safety, efficiency, and reliability, as well as, enable monitoring and controlling it in a real-time This is just the minimum threshold of changes that can be made with intelligent automation and digital transitions in both the manufacturing and processing industry, which frames the use-case-based sections that follow [18].

AI ON THE FACTORY FLOOR: REDEFINING MANUFACTURING ECOSYSTEMS

Artificial Intelligence (AI) is inaugurating a paradigm transformation in the present manufacturing ecosystem since it is more intelligent, faster and extremely productive. Under the increased global competition and the requirements of the customer being more differentiated and of higher quality produce, the manufacturer is turning to AI as a way of making the processes as efficient as possible with minimum down-time, a higher quality, and flexible and data-based production lines. The part explores the nature of AI application in the manufacturing environment. One of the most important peculiarities of the manufacturing activity is a production planning and scheduling [19].

The unpredictable situations such as high and low demand of products and breakages or delays on the supply front cannot be answered in an intelligent manner by conventional processes. With the help of such AI algorithms as optimization and reinforcement learning models, several constraints and variables can be analyzed quickly to generate the best production plans. They can also react in real-time with new information and this helps the manufacturers to achieve high throughput, less lead time and less wastage of resources [20].

Reactive maintenance based or scheduled maintenance based equipment maintenance strategies are currently being (or are soon) converted to predictive maintenance by an AI. Machine learning models will use the data collected into sensors placed onto the equipment to detect the earliest magnitudes of wear or vibration anomalies or thermal anomalies. With the prediction in advance of the failures, manufacturers avoid any unexpected downtimes and reduce the amount spent on overheads and maintenance cost and extend equipment life [21]. Fault detection and diagnostics are usually carried out using such mechanisms like support vector machines, decision trees, and deep learning networks. On-line defect inspection and detection relatively established use of AI-based computer vision involves real-time inspection of defects. The cameras are high resolution and they are joined with the deep learning models that identify surface flaws, dimensional flaws or color mismatches with the accuracy that is higher in a lot of cases than a human inspector. More than that, AI permits continuous learning of new variations of products; consequently, it is implanted into high-mix, low-volume production lines. These will reduce the wastages, lead to the standardized product, and raise the customer's satisfaction of the product [22].

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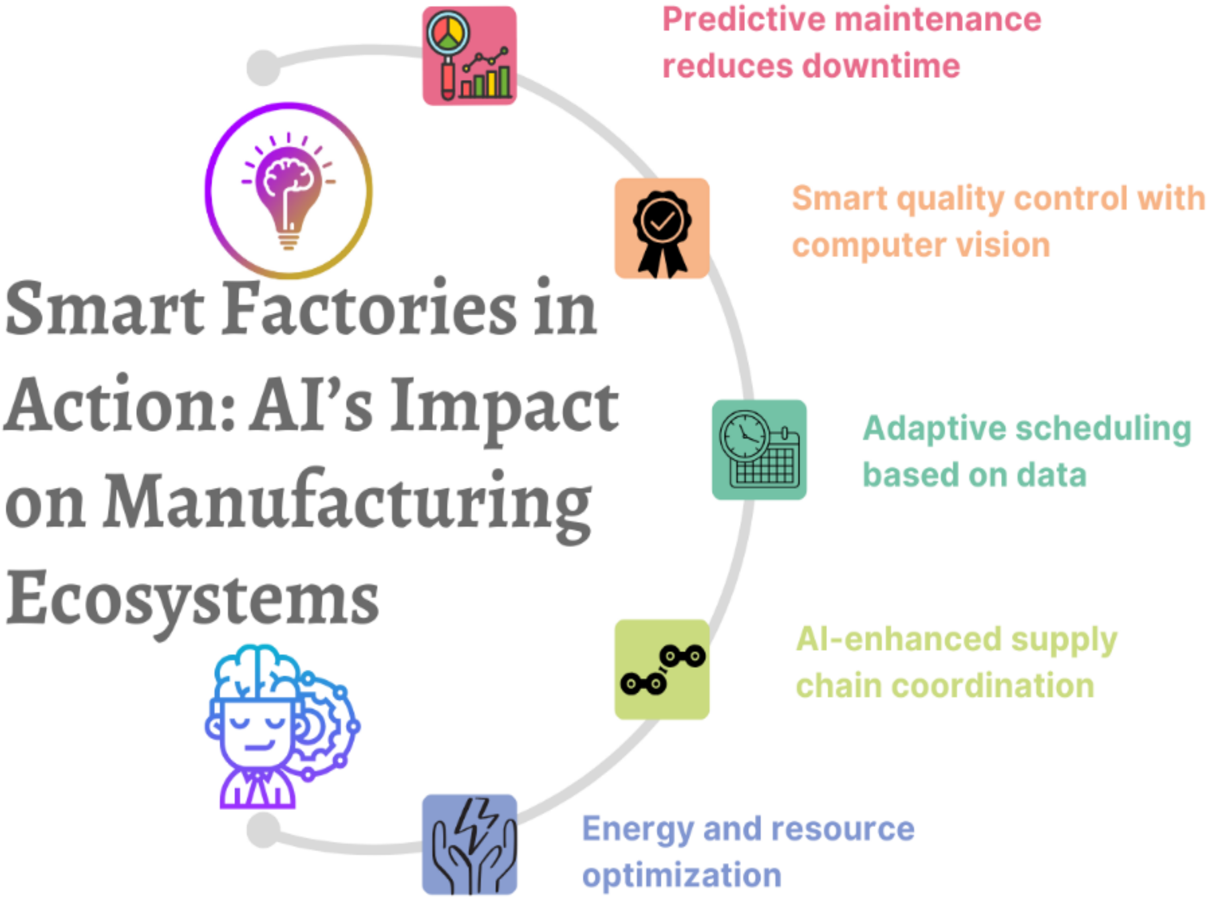

Figure: 1 showing AI impact on manufacturing ecosystems

The modern industry can hardly even imagine its life without industrial robotics, and AI is the complement to robot abilities in terms of the constructive adaptation and coordination of movements on the basis of the vision and in terms of the human being-robot exchange. Through the AI, the robot can learn to identify parts, respond to a changing environment and even new assembly tasks through use of demonstration or simulation. The proficiency of auto mobility gets augmented as well as found in precision/customization/variable-input jobs [23].

AI matters off the factory floor. The AI tools in the supply chain management can help to predict the demand, management of inventory, and management of logistics. The real-time analysis and modeling of such data with the help of AI allow making better decisions in the process of procurement, warehousing, and distribution activities. This increases supply chain resiliency and avoids cost incurred in the event of an overstock or stock-out [24]. The above applications only show how AI can be used to enhance each of the following aspects of manufacturing (planning, production, quality, and logistics) until it transforms factories into smarter, lean, and more agile.

INTELLIGENT PROCESSING: HOW AI POWERS INDUSTRIAL FLUIDITY

Processing industries such as food and beverage processing, pharmaceutical processing, petrochemicals, chemicals, pulp and paper industries and material industries are very important in terms of processing precision, consistency and safety. The issues of these industries tend to be characterized by complicated and nonlinear and also dynamic systems in which real-time decision making is essential, the control is quite close [25]. The Artificial Intelligence (AI) processing has turned into some form of revolution that helps in maintaining quality, streamlining the operation processes and enhancing effectiveness in the activities of businesses. The chemical, thermal and mechanical processing systems involve sophisticated units that are difficult to model using the traditional methods of mathematics [26]. Specifically, such techniques as machine learning (ML) and deep learning (DL) are quite helpful resources which enable model-driven data-driven modeling informed with the help of AI. These types have the capability to model complex input/output behaviour on past process information and have the capacity to generalize on the behaviour of the system in different situations. By default, you will be able to enhance the processes making use of AI and maximize the output of the cultivations, minimize the consumption of energy, and retain the specifications of the products [27].

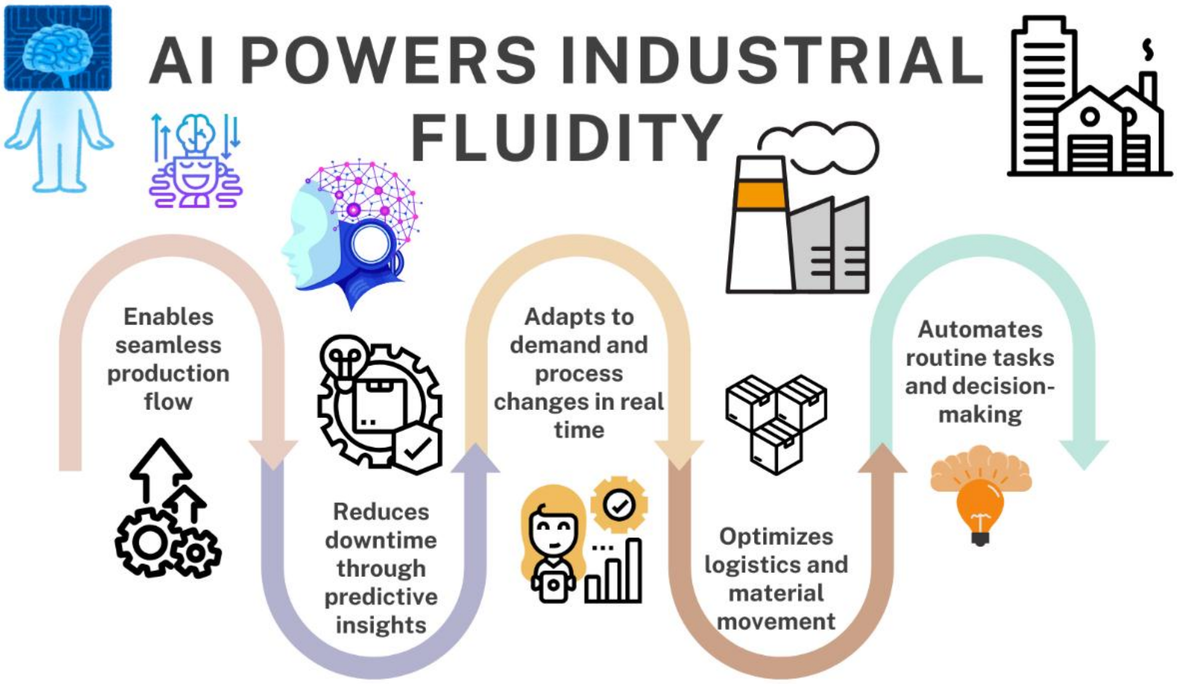

Figure: 2 showing AI powers industrial fluidity

As an example, the AI can be used in chemical production, as it has been used to optimize the condition in the reactor and mixing rates. When applied in oil and gas industry, it helps in the optimization of efficiency of the distillation process of crude by monitoring the variation of temperature and pressure. A majority of the processing activities would require control and monitoring of the temperature, pressure, flow rates and concentrations. Such control systems can be even more active with the help of AI with the use of data given by the industrial IoT sensors and real-time decisions [28].

Dynamic performance The given AI predictive control algorithms may adjust parameters of the process so that to adapt to process disturbances or material changes, which the traditional PID (Proportional-Integral-Derivative) controllers cannot perform effectively. Ai is also developing soft sensors, electronic devices that only estimate measures on is-tough-to-measure qualities depending on the collection of currently available data without relying so much on the actual gauge installation or slow gauge resolution [29].

With batch processing manufacturing (e.g. pharmaceutical, specialty chemicals) where both precision and compliance are all that matters, AI ensures uniformity between batches because it learns based on past data and detects aberrations. In a continuous processing industry (e.g. oil refining, pulp and paper) AI can also be used to improve stability and throughput due to the

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availability of adaptive control systems and the ability to anticipate process drift or wear of areas. It has been found out that the processing plants are a site that essentialisms the safety in the midst of the usage of dangerous substances and hazardous work [30].

The condition of equipment can be tracked by AI systems as well as identify any leakages or abnormal emissions, and predict disastrous breakdowns. A conjunction of anomaly detection in real-time and the application of AI to managing alarms should also allow companies to hide accidents and guarantee compliance with regulations with more assurance. The potential of the use of AI in processing industries is world-changing as these industries are growing smarter, more adaptive, and data-based and the benefits of such a revolution cannot be confined to a single side of the process addressing productivity, quality, safety, or sustainability [31].

FROM PROOF TO PRACTICE: REAL-WORLD ADOPTION AND IMPACT

As it is displayed in practice, there is a high value of the use of Artificial Intelligence (AI) in the spheres of production and processing in the solution of the operational issues, improvement of the business performance, and the development of new solutions. In this section, the most significant case studies and industry use cases of applying AI technologies by businesses operating in various sectors are given [32]. Most of the leading automotive industries such as BMW, Toyota, and General Motors incorporated AI long ago, to make production more efficient and reduce unwanted downtimes. Using an example of BMW, they are embracing the power of AI-based programs to help in defining the use of machine sensors in the prediction of part failure. This form of predictive maintenance eliminates unforeseen breakdown in manufactured products by contributing to costly shutdown in the production line. Besides, Toyota has already brought AI-based analytics to the welding and the painting departments to optimise materials usage and ensure standard quality products [33].

Samsung and Fox discovered the application of artificial intelligence (AI) powered computer vision in detecting of micro-defects on circuit boards and on components in the manufacture of electronics where precision is everything. These systems can verify thousands of items per hour and identify issues that cannot be noticed by a human person. The AI models retain the ability to identify any minor variation in the surface quality, solder connection, and alignment, thereby reducing the defect rate further, and raising the overall product reliability [34].

Companies that are associated with food pie, e.g., Nestle, Coca Cola, etc. have embraced AI in the food they produce where there is quality control, machines in the production processes and inventory. Nestle exploits machine learning to learn the sensory information to guarantee that the flavor of one batch has the same flavor as the other batch [35]. Coca-Cola resorts to AI as a means of forecasting their demand, the better sourcing of their ingredients, and their logistics. These systems reduce wastes, improve on sustainability, and are well positioned to deal with shifts in fancies of consumers [36].

Pfizer and Novartis are pharmaceutical institutions using AI in the control of batch processes, drug development, and regulatory compliance. With AI models, one can ensure that the best of the environmental conditions under which the production process goes on can be maintained thus ensuring a stable potency and safety of the drug. AI technology in research and development is applied in accelerating the search of molecules, comparing of large data sets and chemistry modeling. Such apps increase speed in the release of goods and reduces the cost of production and, at the same time, it reduces human error [37].

The modular, low-cost solutions are also entering the AI age with the SMEs. As an example, some middle-sized companies working in the textile industry use energy management systems with artificial intelligence to control the consumption of the utility services and reduce the costs. Other companies exploit AI-as-a-service in a cloud-computing environment to conduct demand prediction and stock optimization without substantive investment in hardware [38]. These applications highlight the versatility of AI in many aspects and applications. Whether it is the optimization of processes in the manufacturing lines of big, multinational organizations or the streamlining of the

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work of small businesses, AI demonstrates as a flexible tool with an enormous effect on the modern industrial environment [39].

BREAKING BARRIERS: SYSTEMIC CHALLENGES IN INDUSTRIAL AI ADOPTION

Despite the recent high application of the Artificial Intelligence (AI) application in the manufacturing and processing business, there are certain barriers and limitations of its application on a large scale. They run across technological, organizational, financial and moral grounds. Being aware of such barriers is relevant to the prosperity and sustainability of the stakeholders with enthusiasm toward successful implementation of AI solutions in the future [40]. AI applications are characterized by heavy reliance on large volumes of good data during training and operation. However, the quality of available data, in most industrial plants, is poor, records are missing or they are unstructured. The acquisition of legacy machine data is not always consistent and easy because modern sensors are not usually installed. In addition, information across different systems is neither interoperable nor usually standardized and this leads to integration issues [41].

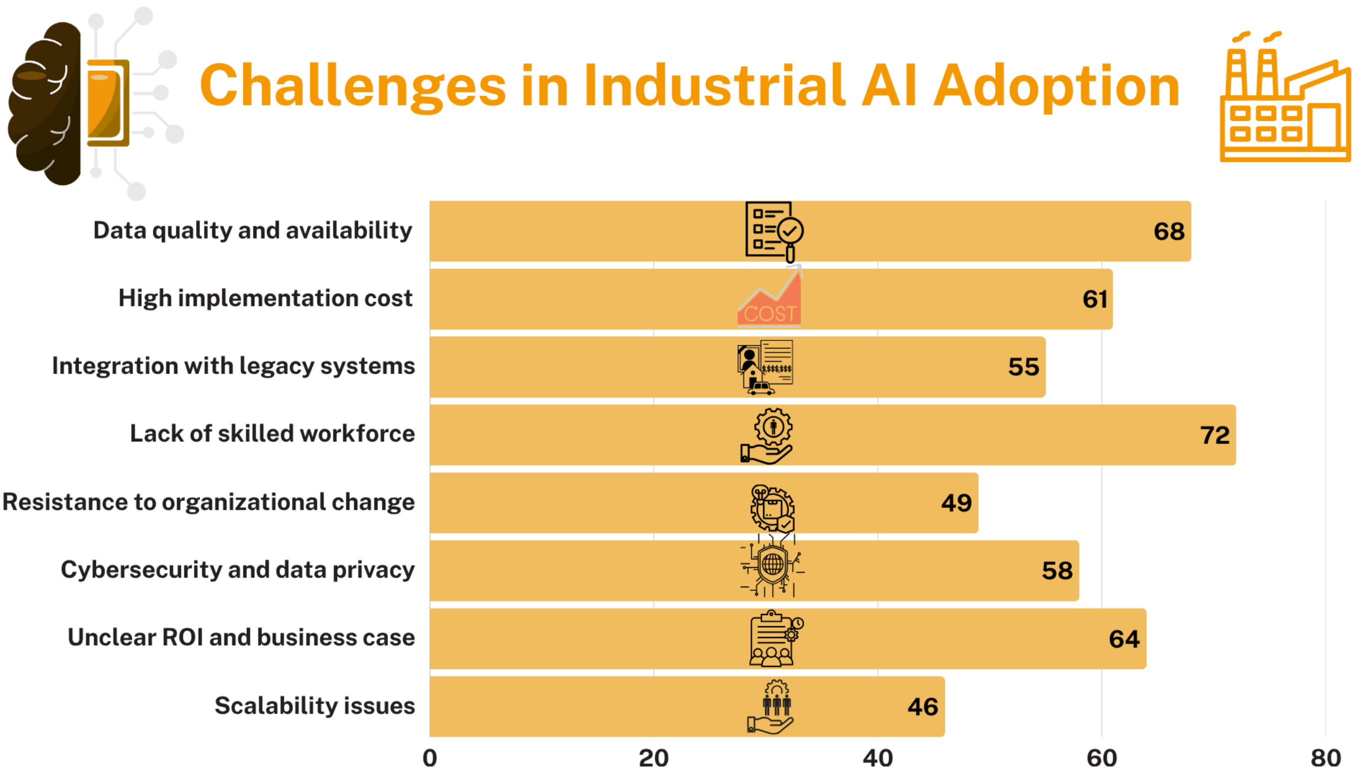

Figure: 3 showing Challenges in industrial AI adoption

In addition, such burning concerns as data security and privacy arise. AI models often require the access to the sensitive information about the work process, and, without the strong cyber-security systems, there is a high likelihood that systems are going to be susceptible to cyber-attacks or data leaks. The cost of installing AI in a single installation might be high, particularly to the small and medium enterprises (SMEs). Such costs include bar-code upgrade, sensor fitment, software programming, cloud and training of the employees. In spite of the enormous advantages associated with long-term focus, it is not an instant dividend since the benefits of the investment are typically not accounted in terms of returns on investment (ROI); thus, cash-strapped organizations will not easily afford the cost [42].

In addition, the companies are not always certain of the AI technologies that they would apply and, without any planning, their investment would fail to bring the required performance. When it comes

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to the implementation of AI, it tends to be a shift in capability of the personnel. Such existing employees may lack the technical expertise either to operate or to operate in the case of conventional industries with the AI systems. This creates a rising need of reskilling and up skilling at fetish of time and expenditure [43].

Resistance is another change barrier. The employees may view AI as a job killer mainly in those jobs that involve a lot of manual tasks or those in which a job is repeated. With improper change management and communication, such fears would result in either low adoption levels or resistance within an organization. Industrial application of AI is complex in its nature. The flows, all equipment and all working conditions in both the facilities are unique and the development of the generalized solutions of the AI is a difficult task [44]. They often require customizing and this is in addition to time which inflates the development cost. Besides, there is the issue of large-scale deployment of AI pilot programs; at the mass production level; technically and organizationally. There are many cases when, due to inability to scale, misalignment with business goals, or absence of appropriate infrastructure, quite a number of projects remain at the stage of tests [45].

The ethical side can no longer be disregarded because the AI systems are going to be more autonomous. The matter of transparency, accountability, and equity in decision-making also must be raised, and it is important in the situation where AI is making important decisions during the operations [46]. Besides, the field of regulatory compliance is evolving, even further, and what was considered a regulatory standard in the context of industrial application of AI is shifting, thereby confounding any company willing to comply. Admittedly, AI is disruptive in the manufacturing and processing sphere, so it is significant to reduce the described challenges so as to achieve dependable, moral, and dynamic implementation [47].

INDUSTRIAL AI: EMERGING DIRECTIONS AND RESEARCH HORIZONS

Artificial Intelligence (AI) has already become a tendentious trend, and yet the sphere where it will be widely used in the future the manufacturing and processing industries application far outweighs all other spheres of its application. The future will not only focus on the enhancement of the performance and effectiveness of the organization but also on the encouragement of the innovation, sustainability, an resilience. Here, the important trends and research directions are outlined to be followed in the process of coming up with the next wave of industrial AI [48]. The biggest one is hyper automation, i.e. the use of AI and/or other technologies such as robotic process automation (RPA), Internet of Things (IoT) and other powerful analytics to automate ever more complex operations. The new-gen factory and processing establishments will strive to be autonomous on the whole with the systems being able to optimize, recuperate, and modify devoid of the need of human supervision. Such studies are in progress, including how the entire production ecosystem can be controlled by the digital control towers using AI [49].

Edge AI, or code that executes AI code on local machines, or devices or sensors, is emerging, as industrial processes become subject to an ever-faster response. Edge computing has the potential to decrease the latency and enhance data privacy compared with cloud-based AI because data is processed close to the source. This concerns a lot in regard to the industrial manufacturing lines that are fast, or the lines that are safety oriented because things have to be done in seconds [50]. One direction will be Explainable AI (XAI), i.e. the research question that will focus on making the AI decisions more interpretable to those operating it. The trust aspect of AI is needed in manufacturing, especially in the case where it will take life-altering decisions. Production of AI models which would defend their actions, outline factors used in making decisions and rationalize their reasoning will become a necessity in regards to compliance and confidence of the decision maker [51].

New technologies featuring AI will be capable of becoming the key players to promoting sustainability. The scientists are also researching the contrasts that can be brought about by the use of AI to utilize less energy and better the energy at its disposal and squander with less of it in the course of the industrial processes. Additionally, AI models that require low energy and therefore are

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more environmentally friendly and deployable on edges are also becoming fashionable [52]. The future AI apps would probably be seen as an add-on to the human capabilities more than a labor substitute. The worry-free human-AI collaboration will happen through intuitive design interface, augmented reality (AR) and voice-based systems that will enable workers to use AI hard drives. The present investigations are also being guided to adaptive system of AI that learns the preferences of the consumers and improves over a period of time [53].

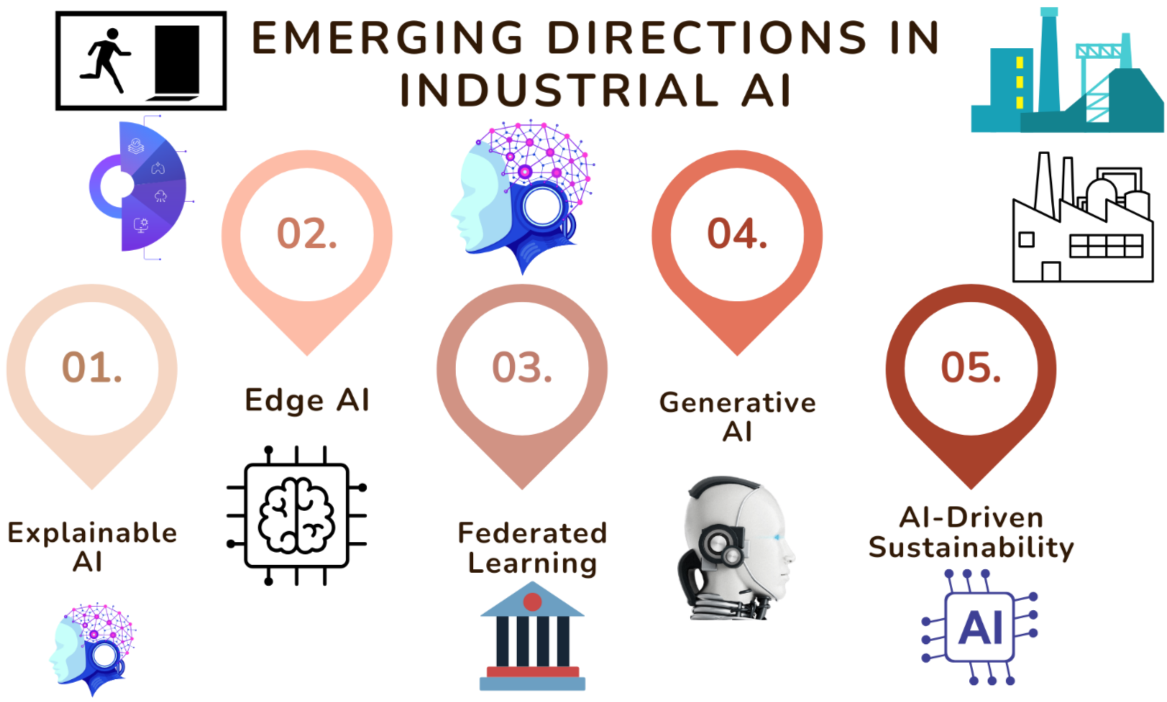

Figure: 4 showing emerging directions in Industrial AI

Due to the increasing use of the AI application, the development of international rules and laws will be of utmost importance. These will entail data governance, algorithm accountability and interoperability across them. The policies are being developed by research agencies and governments to ensure that the AI is used in the industry ethically and safely [54]. The future of AI manufacturing and processing is interactive, differentiated, and very well integrated with human, environmental, and technological systems, and this is what effects the smart industries of the future.

CONCLUSION

The coming of the artificial intelligence (AI) to the manufacturing and processing industries is a noticeable change in the Industrial processes representation, route and optimization. As the industries are struggling to improve on their efficiencies, reduce their cost, assure quality and meet the ever increasing business requirements in the market, AI is turning to be a driver force that has the potential of delivering value contribution that is quantifiable on the value chain. The specified artificial intelligence technologies, machine learning, deep learning, computer vision, natural language processing, and reinforcement learning have been already demonstrating their capabilities in improving an impressive range of processes in the sector. Time management, process optimization in real-time, intelligent administration of quality and showing smart supply chain management are just a few of many applications of the use of AI; it is not simply streamlining processes available today but unlocking an entire new range of capabilities that could not be applied to traditional systems previously.

Such smart production planning, resource use and faster response to a shift in demand or upsets are possible through the use of AI in production. To take an example, we can speak about AI-driven

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robotics that is changing assembly lines and adding more fluidity and collaboration. In the meantime, in the manufacturing powerhouses, such as chemicals, pharmaceutical industries, and food production manufacturing industries, the AI contributes accuracy and repeatability to high fidelity control systems, virtual monitoring and virtual sensors, as well as active monitoring processes. This is particularly required simply in case the process is sensitive, harmful or controlled.

The given case studies all highlight the real-life application of AI to the industry that has brought significant transformations in the aspects of quality, productivity, and continuation of an organization. Not only are big companies applying predictive analytics to make more efficient international supply chains, but also small- and medium-sized companies can enjoy cheap and cloud-based AI to help them cut on energy or find faults; living up to its reputation, AI proved to be enough versatile to serve any company. However, the path of accomplishment of AI participation is not hindrance free. It would have to be made successful by resolving such considerations as the quality of data, cost of implementation, preparedness of workforce and ethics. To this day, one can find more than enough organizations that are forced to work with antiquated infrastructure, fragmented data systems, and stagnant change, factors, which are likely to hinder AI integration. And above this, the industrial conditions, to which AI must be applied, are complex enough that the solution that it suggests has to be not only competent but treatable, safe, and expandable.

Some trends exist to establish the following phase of AI in industry in the future. The most popular are going to be edge computing, explainable AI, human and AI collaboration, and sustainable models of AI. There will be an unlimited growth in concentration on the creation of smart yet clear, robust, and environment and society value-aligned systems. The multi-stakeholder research involving academia, industry and government will be very instrumental in the development of standards and regulations that will support safe and ethical use of AI. Moreover, they will not eliminate human participation in an industry where an AI is installed. It is easy to achieve automation of routine and complex and the timing by providing AI, judging, innovation, and awareness of the environment cannot be replaced with anything. Therefore the most efficient and sustainable solution would be likely to be a hybrid one where AI is not intended to replace the human effort but rather add to it.

AI reimagines the boundaries of what can be done in the processing and production. It provides the ways to relax into the new paradigm of predictive and autonomous operations to become smarter, quicker, and more dynamic. Since the tendency to attain full digitalization will occur in the future and cannot be expressed in a chronological manner, the importance of AI is rather great, and it cannot be ignored. With due investment in technologies, organization of adequate teams and a design that require innovative thinking, industries can employ AI as the secret to future success in the industry.

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Volume 1, No.6 April, 2024
ISSN 3025-7409 (Media Online)
Hal 879-891

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