International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 02 , February - 2026

Applications of Advanced Mechatronics and Artificial Intelligence in Manufacturing: A Review

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Abstract: **The adoption of Artificial Intelligence in manufacturing systems is causing a major change in manufacturing. In the Industry 4.0 environment, AI assists in data-driven decision-making, optimization of the processes in real-time, and automation. This paper analyses the use of AI in the manufacturing process highlighting the advantages, issues, and dangers in the actual industrial settings. The study adopts a qualitative research approach, which consists of industrial case studies and peer-reviewed journals. Some of the AI applications discussed in the review include predictive maintenance, quality control, process optimization, supply chain management and robotics. The findings suggest that the application of AI increases the operational efficiency, product quality, equipment reliability, and time-to-market. The research finds that in spite of the difficulties associated with the qualities of the data, system integration, high implementation costs, workforce skills, and model transparency, AI still has great potential in improving manufacturing in situations where such initiatives are backed up by suitable strategies, trained human resource, and standardized frameworks of integration.**

Keywords: Artificial intelligence, Machine learning, manufacturing, predictive maintenance

INTRODUCTION

The process of manufacturing refers to the transformation or change of raw materials to finalized goods by the use of equipment, human abilities, technology, machinery and chemical processing [1]. Artificial intelligence is revolutionizing all industries, one of them is manufacturing, AI has become a key enabling technology in modern manufacturing, supporting transition toward Industry 4.0 and is an element of the basic concept of Industry 4.0. This transformation happens by enabling real-time data analysis, process optimization and improved decision-making. Main AI applications in manufacturing include predictive maintenance, inventory management, quality inspection, fault detection, product optimization and process monitoring. These applications help companies increase efficiency and reduce costs. Across different industrial sectors, including food processing, electronics manufacturing, autonomous vehicles, batteries, robotics, renewable energy, AI has demonstrated the ability to improve product consistency, enhance accuracy, and reduce material waste. The integration of AI with robotics and intelligent systems like machine learning, IoT, digital twins, computer vision and natural language processing allows flexible automation, human-robot collaboration and adaptive response to shifting production demands. The synergy between AI, robotics and sensors is a key driver in modern manufacturing systems. Despite the benefits, general adoption of AI in industry also faces challenges. Issues like data quality, system integration complexity, model transparency, high costs and the need for skilled personnel limit implementation and make it more difficult. Many AI applications are implemented without standardized frameworks, so the absence can complicate interoperability and collaboration among different systems for design, validation and lifecycle management. This paper aims to review practical applications of AI in manufacturing through the literature and case studies. The study focuses on implementation strategies, benefits, challenges in real industrial companies and risks. The outcomes indicate that AI can significantly improve manufacturing processes by enhancing quality control, operational efficiency, shorten production time and time-to-market, providing guidance for successful adoption of AI in manufacturing systems.

2. RESEARCH METHODOLOGY

This study adopts a qualitative research, based on literature and case study research methodology, with secondary data collected from peer-reviewed journals, industrial and related technology websites, so the review is structured around analysis of journals from open-access publishers, mainly collected from google scholar, international journals and practical industrial case studies in order to provide a widely comprehensive overview of present AI application and practices in manufacturing. The approach of combining academic research with real-world industrial case studies following a narrative literature review research enables exploration of both theoretical and practical advancements of AI in manufacturing. Only sources directly addressing AI in manufacturing systems were selected based on relevance, clarity description, publication recency and accessibility. To ensure a structured analysis the reviewed literature is organized into thematic categories. Recent studies show that artificial intelligence is widely applied for product enhancement and manufacturing optimization. Specifically, according to [2], for autonomous vehicles AI supports localization, perception and decision-making. AI enhances battery management, SoC (state of charge) and SoH (state of health) evaluation in lithium-ion batteries for EV (electric cars) [3]. Based on [4,5], for the robotics part, AI improves learning, robotic autonomy, perception and integration of cognitive AI capabilities into robotic systems. AI enables predictive maintenance and energy optimization as mentioned in [6,7] for renewable energy systems. According to [8], the traditional steel industry manufacturing is making a transformation through the enhancement of predictive maintenance, process optimization, quality assurance and supply chain efficiency. [9] and [10] mention the transformations the semiconductor manufacturing processes are having through AI utilization, by supporting design automation, process optimization, defect detection, and yield improvement. According to [11], main implementations of AI for product enhancement include autonomous vehicles, battery, robotics and renewable energy, on the other side of AI for enhancing the manufacturing processes include steel and semiconductor. Autonomous driving systems mainly employ deep learning models for perception and localization tasks such as road and pedestrian detection. Road and pedestrian detection are mainly addressed using CNN (convolutional neural network) image processing, enhanced through multi-sensor fusion. Latest studies show that for a safer autonomous vehicle operation multiple sensors must be combined with deep learning frameworks to improve detection accuracy and localization performance by integrating data from cameras, LiDARs and radars. Figure 1 shows AI in autonomous driving.

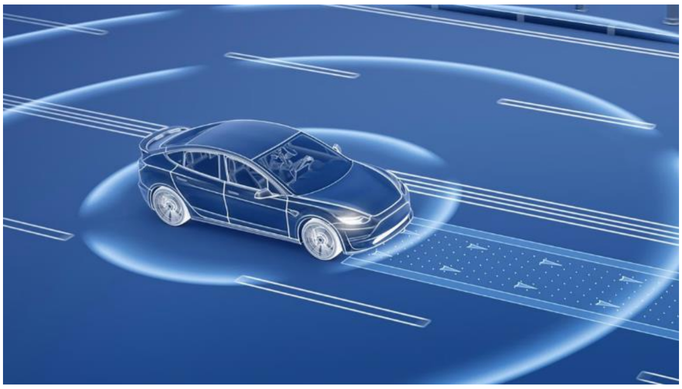

Figure 1 AI in autonomous vehicles [12]

The electric vehicles and hybrid electric vehicles mainly use lithium-ion batteries due to their long cycle life and high energy density. Battery management system relies on data-driven and machine learning approaches to estimate key health indicators such as SoC (state-of-charge) and SoH (state-of-health). Machine learning and deep learning can achieve high estimation accuracy and outperform traditional methods. Both SoC and SoH estimation have been conducted using different models, learning techniques and approaches. SoC estimation has been approached with GPR (Gaussian process regression), random forest etc., outperforming NN, SVR etc. On the other hand SoH evaluation has been completed using ML techniques and proved to be more competitive than SoC evaluation. Figure 2 shows AI in batteries.

Figure 2 AI in batteries [13]

Robotics play a central role in automation by realizing AI decision-making in manufacturing systems. Deep learning models, especially CNNs (convolutional neural networks) and RNNs (Recurrent neural networks) are effective in complex environment allowing robots to perceive, recognize objects and learn dynamics. Additionally, reinforcement learning has appeared as a powerful approach to enhance robotic autonomy, adaptability and performance in environments. Figure 3 shows AI in robotics.

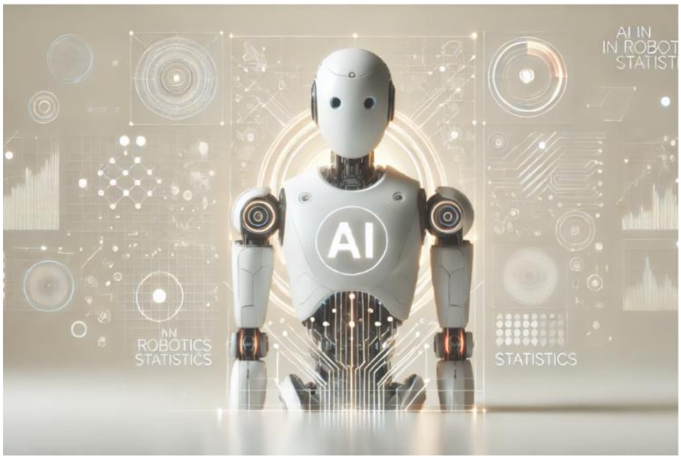

Figure 3 AI in robotics [14]

Renewable energy systems, specifically wind turbines and photovoltaic systems, rely on AI fault detection and diagnosis to improve reliability and efficiency. Deep learning models like CNNs, RNNs, LSTMs (Long short-term memories), DCGANs (Deep convolutional generative adversarial networks), GRUs (Gated recurrent units), GANs (General adversary networks) and residual networks are widely used to analyze multi-sensor data fusion for further enhancement of defect detection accuracy. Figure 4 shows AI in renewable energy.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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Figure 4 AI in renewable energy [15]

AI is applied across steelmaking processes, like ironmaking, rolling, casting, galvanizing, to improve fault detection, process control and product quality. In order to the enhancement of precision, efficiency and monitoring capabilities, machine learning and deep learning models such as ANN (Artificial neural network), CNN, LSTM, SVM (Support vector machine) must be enabled for the prediction of molten iron quality, hot metal temperature, casting defect, strip shape and coating thickness. Figure 5 shows AI in steel industry.

Figure 5 AI in steel industry [16]

AI's role in manufacturing of semiconductors is the improvement of defect detection, process monitoring and anomaly prediction. For the accurate classification, pattern recognition and segmentation of wafer defects, image-based CNNS, CAE (Convolutional autoencoders) and encoder-decoder networks must be included. Signal-based approaches leverage sensor data with CNN, LSTM models to detect faults early, handle noise and data drift. RGRN (Randomized general regression network) is used for mixed-defect classification combined with CNN. Self-attentive networks are inspired by transformers, applied to variable-length sensor sequences for early fault detection, Hybrid CNN + XGBoost, CNN extracts features, XGBoost classifies complex defect patterns. There exist three main stages for defect classification where these defect classifications focus on single defect forms. The first stage, where to remove the noise in raw images, a spatial filter is applied. Secondly, for the identification and separation of defect patterns that are mixed and single, a splitter based on the gained information generates rules. Then, the classified data of mixed and single defect patterns are fed to different models, single defect data is fed to RGRN, while mixed defect data is fed to CNN at the same time for training and testing. The separation method is more effective than DL techniques. Figure 6 shows AI in semiconductor manufacturing.

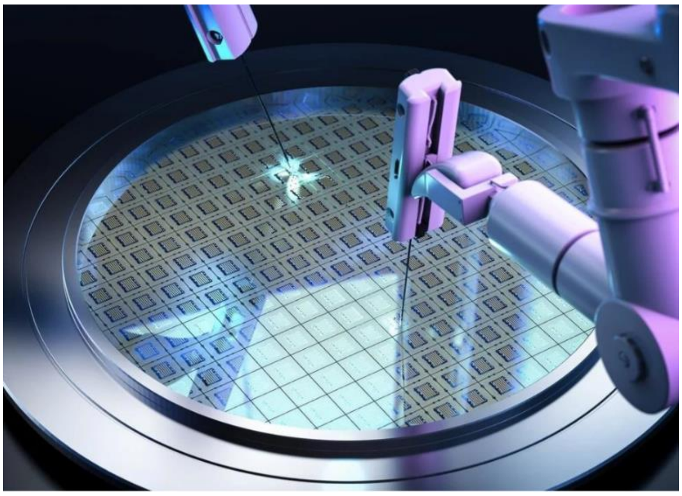

Figure 6 AI in semiconductor manufacturing [17]

Based on [18] and [19], machine learning is divided into three subtopics which are supervised learning, reinforcement learning and unsupervised learning. Supervised learning involves the machine learning algorithm being trained on data consisting of input features with the labels. On the other hand, during unsupervised learning, the algorithm is only trained using input features and no labels. Machine learning together with predictive analytics, computer vision, robotics and automation, natural language processing (NLP), digital twins, IoT, and reinforcement learning form the core AI technologies in manufacturing. Machine learning indicates a group of algorithms that analyze historical and real-time data to identify forms and make judgments toward solving specific tasks by using the data that are related to the specific tasks, predict outcomes. ML is mainly used for predictive maintenance, demand forecasting, defect detection and process optimization in manufacturing. Predictive analytics is used for equipment failure prediction, supply chain optimization, and production planning in manufacturing. Computer vision allows automatic quality control, defect detection and assembly line tracking. Robotics are mostly used in the fields of assembly, packaging, wielding, and automatic handling of repetitive tasks. Natural language processing (NLP) is the interpretation and generation of human language for communication, in the manufacturing process, it is supported by chat bots that assist in production, report generation and report analysis (maintenance logs). Digital twin creates digital models of real systems to be stimulated and optimized and in manufacturing it is used for live process optimization, predictive maintenance and factory layout stimulation. Through IoT, sensors and devices are connected to collect and transmit live data, in manufacturing IoT is enabled for the monitoring of industrial equipment, recording of energy used, and managing the environmental conditions in real-time is a comprehensive solution to operational management. Reinforcement learning, through trial-and-error exploration of the action space by reinforcement signals, finds the efficiency of maximally efficient strategies which maximize long-run performance results, in manufacturing, reinforcement learning allows the integration

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 02 , February - 2026

of robot navigation, adaptive control over processes and dynamic scheduling is a critical innovation in modern digital automation of industry. The benefits associated with the introduction of artificial intelligence into manufacturing processes are reflected in the increased efficiency in its operation, enhanced accuracy and better decision-making. One of the companies utilizing AI in manufacturing is Tesla with its AI robots for the assembly of vehicles, catching unmatched accuracy and speed, and another company is Unilever, they have implemented artificial intelligence based on optimization of the supply chain, using predictive models to predict demand and reschedule production. Figure 7 explains core AI technologies.

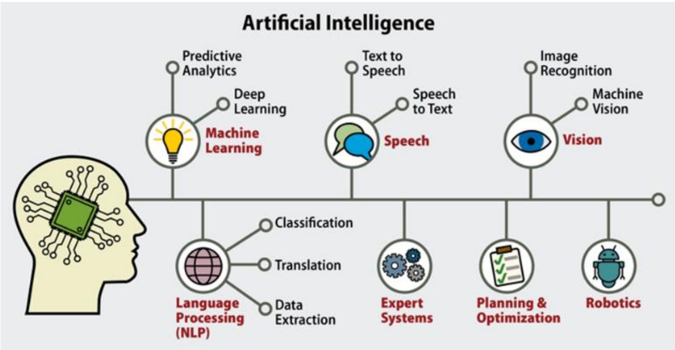

Figure 7 Core AI technologies [20]

[21] mentions that main ML methods contain Extreme learning machine (ELM), Gaussian process regression (GPR), Support vector machine (SVM) and Hidden Markov process (HMP) while deep learning involves usage of deep neural networks like Convolutional neural network (CNN), Fully connected neural network (FNN), Long short-term memory (LSTM), Generative adversarial network (GAN) and Graph neural network (GNN). Worker safety is a challenge mentioned by [22], where AI techniques are transforming safety standards inside manufacturing. The safety of workers in manufacturing is a very important issue because the possibility of material handling, working with machines, and monotonous work are identified as risks. Predictive analytics helps to overcome these risks by analyzing the data in the workplace, classifying accidents, predicting the level of injuries, and making early interventions and informed decisions. Other applications of predictive analytics in worker safety are predictive maintenance and fault diagnosis, workplace environmental monitoring, sustainable manufacturing practices. Another technique is the utilization of computer vision for live intelligent surveillance and enhancement of workplace safety through communication powered by NLP. Through computer vision the whole factory workplace can be controlled and monitored to prevent potential dangers through CCTVs, infrared cameras and sensors, LiDARs, these overcome the traditional sensors that might let pass unnoticed movements. CNN is used as main advancement for computer vision, for example detecting fire. Deep learning models that detect objects are also used, like faster R-CNN and Mask R-CNN, these models are all used for monitoring and detecting hazards. Detection models are used to discern workers and machines, so the collision prevention can happen through live alerts issued by the system if the worker gets near the danger zone of the operating equipment. The system can also detect the posture of the worker, identifying activities, like unsuitable lifting methods or risky bending and trigger actions to prevent injuries. Also, the safety gear can be detected through computer vision if any worker does not comply with the company's regulations by wearing the required safety gear. Figure 8 shows the role of AI in worker safety.

Figure 8 AI in worker safety [23]

Main AI applications according to [24], [25] and [26] include predictive maintenance, quality control, supply chain optimization, inventory management and demand forecasting, energy management, process optimization, human-machine collaboration, data analysis and decision-making, remote monitoring and control, process control and fault detection, data analytics. Predictive maintenance is a preventive maintenance system, which aims at trying to predict the failure of equipment before it occurs and the process of cutting down the downtime and lowering the maintenance costs. Predictive maintenance systems are based on AI, which use sensor data, previous data, and machine learning algorithms to analyze equipment condition and predict possible failures. Artificial intelligence in terms of quality control is applied to the field of product quality inspection and evaluation, it comprises the use of vision systems powered with AI to detect flaws or faults in the quality of the product produced, while machine learning algorithms identify defects or deviations with the established standards, thus only allowing high quality goods to be produced. Algorithms used in quality control include Decision trees, SVM, ANN and RF (random forest). Process optimization is done with an objective of increasing manufacturing efficiency, productivity and resource utilization by improving different aspects of production processes. In the supply chain, AI has been used to optimize the processes of the supply chain by forecasting demand, managing inventory and finding the most efficient routes for transportation while minimizing costs and maximizing efficiency. Artificial intelligence (AI) is also becoming a commonly used feature in the field of energy management to optimize energy use in manufacturing plants. Through the comparison of used forms and creation of specific adjustments in the processes with high energy, AI will help to reduce the costs of the operations. Human-robot collaboration relates to the interaction between the people and robotic systems in the same working areas

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
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whereby the work is done together, the safety and efficiency of the work between humans and machine on the factory floor is supported by artificial intelligence, because the work of collaborative robots (cobots) with AI features allows working jointly with human employees in a factory, taking over heavy or dangerous work. Figure 9 shows main applications of AI in manufacturing.

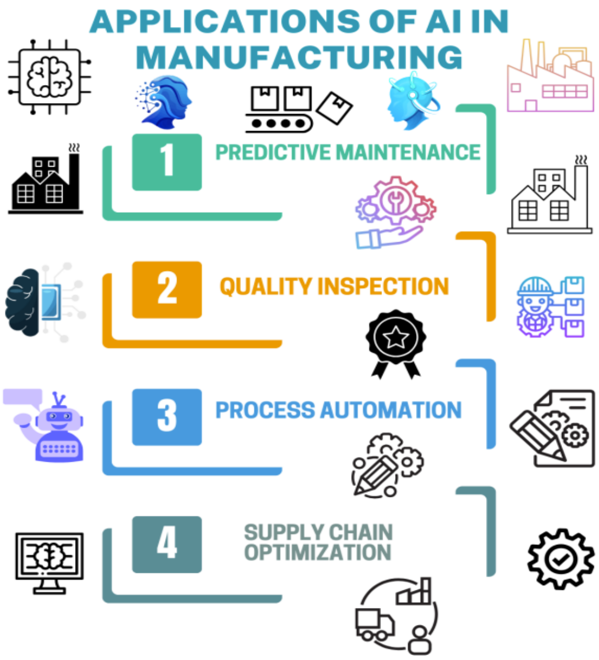

Figure 9 AI applications in manufacturing [27]

As mentioned in [28], a synergy between AI and robotics is transforming manufacturing and automation towards industry 5.0. The synergy between AI and robotics has led to intelligent systems capable of learning and adapting to new environments. These systems are radically redesigning assembly lines, and thus supporting flexible and mass customization of manufacturing systems. Robots that are based on AI have the ability to learn based on information, thus improving their performance in a progressive manner using machine learning. Robots can be equipped with computer vision to sense and interpret their environment and enabling them to do things like object identification and quality control. NLP (natural language processing) also supports human-robot interaction and allows voice commands to be executed so the robot is easier to control. Implementing artificial intelligence (AI) in the production sector has both positive and negative effects, but a number of challenges and threats also accompany it, some of these challenges and risks are identified according to [26]: 1) Embracing AI into real production systems can be difficult, 2) The initial cost of the implementation of AI technologies, including the purchase of hardware, software licensing, and personnel training is significant, which places a challenge on small and medium-sized manufacturers. 3) AI application requires a qualified labor force, therefore, it can be through training of existing employees or hiring new talents with the appropriate competencies which can lead to consumption of time and high costs. 4) Guaranteeing the access to high-quality data, as well as reducing the challenges of data privacy and is still a great challenge. 5) Standards of AI in manufacturing are not yet standardized and so may hinder the interoperability and cooperation between heterogeneous systems and devices. Some of the risks encompass: 1) The decline of autonomy and reliance on AI brings about new cyber-security threats, companies have to protect confidential information and protect their AI systems against hackers and other online attacks. 2) Automation based on AI can replace some jobs, consequently leading to the displacement of the workforce, the inability to organize such transitions in a proper manner might breed social and economic problems. 3) Overtrusting AI without a proper way to fall back on it is dangerous, because an AI system failure can be a result of technical failures or malicious interference and can also affect the manufacturing processes. 4) Also, there is a high difficulty in adhering to the existing and future laws or regulations regarding AI in manufacturing, including data-protection and safety regulations. 5) Some models of AI, especially complicated deep neural networks, are not transparent, and so they are hard to understand. This lack of explainability can be a barrier to understanding and trusting AI-generated decisions. Real-world case studies mentioned in [29] and [30], show how beneficial it was for the companies implementing Artificial intelligence in their manufacturing lines. The first company, ASML, is a chip manufacturer that has utilized AI in manufacturing, 1) ASML produces photolithography machines used in the manufacture of semiconductors. The company was facing the issues of long testing times and long analysis times of calibration datasets. To reduce these problems, cloud-based data storage systems with machine learning analytics were used. 2) Epiroc is a manufacturing company of construction and mining machinery. The company was unable to get replication of thousands of steel grades in multiple manufacturing locations to be consistent. To respond to this, the machine learning models were implemented to predict the steel properties, and AI governance automation to standardize processes. 3) Georgia-Pacific is a company that produces paper and building materials. The company was faced with unplanned equipment failure. Machine learning and computer vision were applied to predictive maintenance used to monitor quality and minimize operational disruptions. 4) Siemens Gamesa renewable energy is a company that produces custom-made wind turbine blades. Manual defects were caused by humans when fabricating the blades. As a result, laser placement that is controlled by machine learning and defect detection by computer vision were introduced into the production line. 5) Toyota is involved in designing and manufacturing of vehicles. Designers were experiencing slow development cycles and challenges in engineering factors into generative design processes. Physical models were used with generative AI systems and engineering constraints to make the designs more efficient. 6) Siemens Electronics Works Amberg is an electronics production plant. There were high levels of scrap, irregular inspection procedures, and unplanned shutdowns in the plant. They introduced applications of predictive maintenance and live quality inspection as well as digital twins in conjunction with control systems to correct these shortages. 7) BMW Group is an automobile maker. The difficulty of production variants and the long process of quality assurance were a serious challenge. To simplify production, digital twins to simulate factory and

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ISSN: 2278-0181
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synthetic data generation methods to train AI models were implemented. 8) Industrial and automotive manufacturing industries are covered under Bosch. The limited annotated information in the detection of defects hindered the training of the AI models. Predictive maintenance models that complemented the use of generative AI were used to make synthetic images that would be used to support defect detection workflows. 9) Foxconn is an electronics assembler cooperating with Huawei. The inspection procedures were too slow and prone to errors through manual inspection. Computer vision and edge AI were used to implement automated visual inspection systems, which use AI powered to increase output and accuracy. 10) GE is the producer of industrial machines and turbines. Monitoring based on rules was not suitable in avoiding unexpected failures. Digital twins, consisting of physical models, were used in combination with machine learning for predictive analytics, reliability enhancement and planning of maintenance.

3. RESULTS

Implementation of AI in manufacturing companies transformed their work progress, real-world case studies shown in [28] and [29] reveal that implementation of AI was beneficial for their sectors. Based on the case studies, the 1st company, ASML, achieved a tenfold increase in efficiency in application development in six months with a 40 per cent reduction in time-to-market. The introduction of artificial intelligence also enhanced the fineness of the semiconductor inspection. The 2nd company, Epiroc, had a reduction of thirty percent on the rejection of customers by the company as well as product returns. The organization accelerated the process of model development and shared data with analytical teams on a large scale. The 3rd company, Georgia-Pacific, achieved a thirty percent decrease in unplanned downtimes credited to the predictive maintenance plans. Monitoring of over 85,000 sensors using artificial intelligence made it possible to detect component failures at an early stage. The 4th company, Siemens Gamesa renewable energy, the reduction of manufacturing defects by twenty five percent enabled Siemens Gamesa Renewable Energy to expect return of investment in about 2.5 years. The 5th company, Toyota, reduced the number of design cycles that had to be done to balance the engineering requirements with initial drawings. Design with AI support enhanced aerodynamic efficiency and supported a long range of electric vehicles. The 6th company, Siemens, at Siemens Electronics Works Amberg, built-in quality rate of 99.9988 was achieved, seventy-five percent scrap cost reduction, thirty-three percent higher shop-floor utilization and seventy to eighty-five percent improved overall equipment performance was achieved. The 7th company, BMW group, reduced the time frame of quality assurance work by almost two-thirds and shortened planning periods. The application of artificial image generation was used to quickly implement AI models in production plants. The 8th company, Bosch, reduced the preparation time of its AI inspection system from nearly twelve months to a few weeks. Inspections of quality became stronger, and the energy efficiency was enhanced. The 9th company, Foxconn together with Huawei, Foxconn obtained the way to seventeen automated inspections at a level of more than ninety-nine percent, the level of defects minimized to a maximum of eighty percent, boosting output and improving the stability of the process. The 10th company, GE, by using the predictive analytics they have achieved a reduction in unplanned outages, longer life of systems, and improved maintenance. Workers have detected these outcomes after AI implementation.

Table 1 four real-world case study companies

Company	Sector	AI application	Results	Reference
ASML	Semiconductor manufacturing	ML analytics, inspection	Development team performance- 10x increase, time-to-market 40% faster, improved chip inspection accuracy	[28]
Epiroc	Steel manufacturing	ML modeling, predictive quality assurance	Customer rejection-30% reduction, faster data sharing, heat treatment ML models developed in 6 weeks	[28]
Siemens	Industrial automation	Predictive maintenance, digital twins	Built-in quality 99.9988 %, scrap costs (-75%), shop-floor utilization + 33%, OEE 70 to 85%	[29]

Bosch	Industrial manufacturing	Generative AI for inspection, predictive maintenance	AI inspection ramp-up reduced from 12 months to weeks, improved quality control, energy efficiency	[29]

4. CONCLUSION

This paper proves how artificial intelligence is a major catalyst to the improvement of the manufacturing industry. The empirical results are in line with previous studies and suggest that AI-based solutions, such as predictive maintenance, quality control, process optimization, and supply chain management, lead to an improvement in operational efficiency, high quality products, and a rise in equipment reliability. Industrial case studies also highlight the reality that such benefits are achievable in real manufacturing situations, which take the form of reduced downtime, reduced defect rates, and reduced time-to-market. In addition, the current findings are consistent with the previous literature sources which outline the barriers to AI implementation including high implementation costs, data quality issues, system integration, competencies in required workforce, and low model interpretability. These obstacles continue to frustrate implementation particularly in small and medium-sized enterprises. In macro-strategic terms, the shift to Industry 5.0 requires the effective implementation of AI to be not only based on the advanced technological platforms, but also on organizational readiness and humanistic models. As a result, further research in the academic community ought to focus on the creation of a coherent system of implementation, the growth of explainable AI models, and the performance of empirical research studies aimed at the sustainable integration of AI into the production setting.

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