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Resilient Manufacturing in the Era of Industry 4.0: Leveraging AI and Edge Computing for Real-Time Quality Control and Predictive Maintenance

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Abstract

Quality is the driving factor of the manufacturing industry. With the advent of Industry 4.0, the integration of advanced sensors, edge computing, artificial intelligence, digital twins, and 3D printing has great potential to achieve resilient manufacturing. The first part of this study addresses real-time quality control with edge computing. A digital imaging system is introduced, equipped with an edge device for real-time defect detection in additive manufacturing. AI promises great potential for achieving zero-defect manufacturing, which was barely possible in the past. Then, as the main structure provider for Industry 4.0, edge computing is described. The computer is used in quality control features of edge computing by real-time cloud monitoring and real-time elasticity for cloud services.

In the second part, a predictive maintenance framework is proposed by integrating the digital twin, advanced data processing, and AI algorithms. AI finally determines the degradation status of products with high confidence to maintain the resilience of the product life cycle. Expensive fault events on products can be avoided with the help of AI-based advanced planning of maintenance at an appropriate time. The approach could mitigate potential risks of shortening lifespan, increasing maintenance costs, triggering catastrophic events, or even causing social impact if combined with real-time edge computing and advanced sensors. Such an approach advances the deployment of the manufacturing industry in the era of Industry 4.0.

Keywords: quality control, manufacturing industry, Industry 4.0, advanced sensors, edge computing, artificial intelligence, digital twins, 3D printing, real-time defect detection, additive manufacturing, zero-defect manufacturing, predictive maintenance, digital twin integration, data processing, AI algorithms, product lifecycle, fault events, AI-based maintenance, resilience, cloud services, advanced planning

1. Introduction

Despite the various promises of Industry 4.0 and the ongoing evolution of manufacturing technologies, there are still prevailing concerns about the disruption of global value chains, particularly evident from the impact of the pandemic. It is not novel for researchers to continuously seek ways to mitigate the negative consequences of globalized international production. Given this consideration, the fundamental issues are in determining how to elevate the resilience of manufacturing businesses in the 4.0 era and what strategies need to be formulated and implemented. There is, however, a relatively recognized lack of research on how to achieve resilience in manufacturing, an already challenging field since it involves a high degree of complexity and the confluence of disparate domains such as business, engineering, and information technology.

Recent advancements in energy-efficient edge computing, combined with the capabilities of connected and self-learning systems, have now opened up the possibility of intelligent factories that have the capability of real-time data acquisition, analysis, and predictive decision-making. This smart production paradigm within the fourth wave of the industrial revolution has been referred to as the vertical integration of cyber-physical systems towards a seamless and efficient approach to handling data. Each stage of the manufacturing process now has the capability of digital detection of potential defects or the generation of process knowledge, despite the type of data involved. Underpinning the work of this paper is the application of embedded artificial intelligence algorithms that are designed to operate at the edge with real-time data for manufacturing. These algorithms have the capability of reasoning, making predictions, and taking autonomous actions to a large extent, critically, at the relevant processing sites while responding to a fault, event, condition, or performance and supporting real-time inference-based decision-making with minimal human intervention.

1.1. Definition and Evolution of Industry 4.0

Industry 4.0, often referred to as I4.0, and the Fourth Industrial Revolution, represents the new phase of industrial processes and manufacturing that leverage digital technologies including the Internet of Things, big data, artificial intelligence, and cloud computing. Industry 4.0 extends the automation process control to a wide range of manufacturing tasks connected via the Internet, underpinned by the fundamental concept of smart manufacturing. Industry 4.0 opens new opportunities across all industries, marking a shift from mass to customizable products, significantly shortening the time to bring new products to market, and dramatically changing the way products are designed, engineered, produced, and maintained. Furthermore, the intelligent use of digital technologies in smart manufacturing allows a smooth transition from mass production to mass customization, meeting the requirements of modern market demand with sustainability and cost-effective solutions.

The introduction of Industry 4.0 has significantly changed the traditional view of manufacturing processes. Over the years, several different industrial revolutions have been documented, characterized by iconic industrial phases and transformations. Each industrial revolution has helped to further modernize traditional manufacturing industries, which have remained essential for a nation’s economic growth for over a century and will continue in the future. Industry 4.0 is the most modern and versatile application example of how connected manufacturing can technically evolve. The expression “Industry 4.0” was first introduced in 2011 at a fair in Germany, which attracted international attention and spread to various countries, becoming the heart of strategies for long-term investment in the field of innovation. Industry 4.0 converges the physical world and cyberspace, forming entities collectively known as cyber-physical systems interconnected through standard communication and networking protocols, to monitor and analyze physical processes and to control physical processes to improve productivity or quality. The synchronous two-way information flow between cyber-physical systems and the humans in charge is ensured by cutting-edge communication infrastructure and advanced data processing that leverage cloud and fog computing functionalities. The achievements linked to these abilities mitigated the reluctance of companies, which have been able to evolve from mass production to specialized and customizable products. The innovative use of digital technologies has allowed small-scale innovative companies to reach industry leaders. The transition from Industry 3.0 to Industry 4.0 was realized by incrementally substituting old manufacturing networks with better modernized and highly automated networks. Initially, traditional machines were not directly involved in this process. The ongoing transition from Industry 4.0 to Industry 5.0 stimulates the involvement of small-scale traditional companies in advanced networks by attracting part of the interest offered by the manufacturing sector from investors. Helping small companies join state-of-the-art networks is essential for maintaining an updated and productive smart network.

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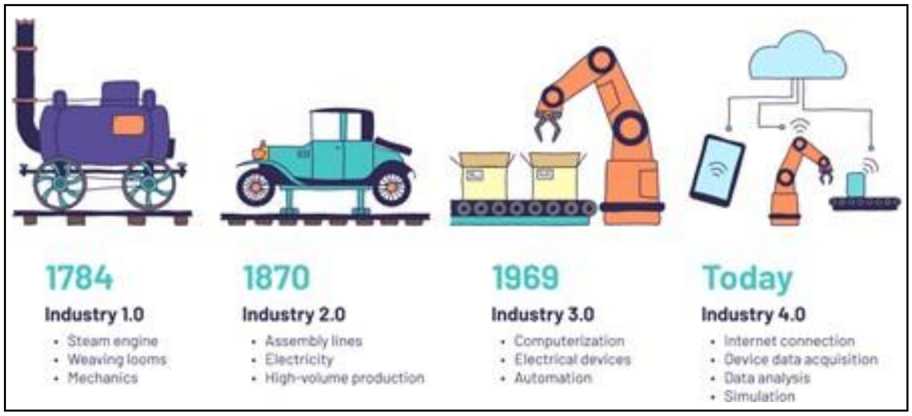

Fig 1 : Evolution of Industry 4.0

$$Q(t) = f(I(t), S(t), \theta)$$

$Q(t)$ = Quality at time t

$I(t)$ = Input data at time t

$S(t)$ = Sensor data at time t

θ = AI model parameters

Equation 1 : Real-Time Quality Control (AI-based)

1.2. Importance of Resilient Manufacturing in Industry 4.0

Today, the manufacturing industry has a significant environmental impact due to high variability in processing performance, complexity of products, and high demands on accuracy. Consequently, the new era of manufacturing, such as Industry 4.0, is an innovation of the manufacturing industry to increase flexibility, improve products, and reduce manufacturing impacts on the environment. To achieve this goal, resilient manufacturing is explored to deal with the complexity and variability of today's products and processes in Industry 4.0. Recently developed symbiotic edge technology has been initiated as the new tool under the current trends of edge computing.

The newly developed Industry 4.0 views manufacturing as a cyber-physical system that enables machine and system movements through mechanical control and connectivity. Machine movements and activities are programmed through distributed computing functions to meet manufacturing system decisions and behaviors. At the shop floor level, edge computers can provide powerful computational capability with real-time response. These developments imply that Industry 4.0 relies on big data, complex intelligence, and symbiotic edge computing to deliver high performance and a smart manufacturing ecology. As a result, the current manufacturing industry expands the scope of manufacturing evolution and strives for resilient manufacturing by proposing combinations of artificial intelligence and edge symbiosis.

2. AI and Edge Computing in Manufacturing

The definition of AI is vague; it may be described as the attributes of higher intelligence found in humans but considered issues in designing machines that include the ability to reason, to find meaning, to learn from meaningful experience, and to apply unseen resources to assume the level of human intelligence. After the introduction of AI, research has been intensified throughout the years, but has not yet found wide applications. On the other hand, the evolution of computing technology made AI capable of executing smart decision support systems. The main purpose of the research is to characterize the relationship between edge computing and AI.

Before analyzing AI and machine learning, we focus on protagonists that are increasing volunteers with edge computing. Edge computing is steady progress in enhancing the outlook and utilizations of cloud computing. Edge computing, AI, and machine learning have revolutionized the utilization through applications that happen at the edge of the network. Edge computing is a distributed computing function within the network, to minimize the essential latency between data sources and browsing networks, thereby reducing the amount of long-distance information association. Edge communications have been introduced in manufacturing, improving performance, acceptance, and quality assurance. They are essential contributors to generation 4.0 for the growth of machine learning applications with delays. To link down to the edge, field equipment designates an edge computer that transforms it into effective arrangements and possibly improves efficiency, proposing quicker feedback by processing minimal specific information.

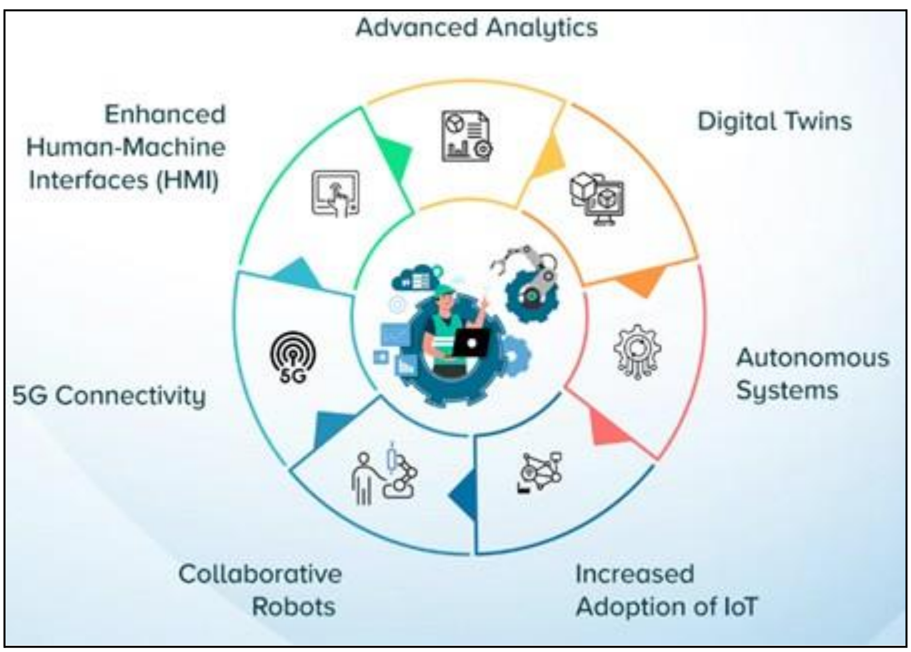

Fig 2 : Implementing Edge Computing in Manufacturing

2.1. Overview of Artificial Intelligence in Manufacturing

Production processes may involve strong variability in raw material attributes, process conditions, energy use, and quality variables, which may be simultaneously correlated. Common attributes of big data, that is, high dimensionality, variability, and forecast capability, do emerge. Several data analytics and artificial intelligence techniques have been adapted for manufacturing and advanced manufacturing systems. Data modeling and data-driven methods have been identified as key elements in the transformation into data-driven intelligent production and manufacturing systems. Process control by easy-to-apply virtual sensors, dynamic fault prediction, and maintenance, design for disassembly, and design for zero defects in manufacturing have been addressed by various data-driven soft sensing and data models, currently with a strong focus on spatiotemporal methods.

We note that standard data are periodically collected in static prediction scenarios, in which the prediction is performed at once for a future horizon. In the literature, pioneering works concerning data-driven applications in the production environment date back to the early 1990s. At the beginning of the new millennium, tools for process state estimation using multiple linear regression, principal component regression, support vector machines, neural networks, and recursive partial least squares in the presence of unbalanced, correlated outliers, and noise data have been developed. Post-optimization techniques for product and process quality prediction based on ground truth and regression techniques for non-destructive characterization of refractory corrosion or cold beef cuts inspection have also been formalized.

2.2. Role of Edge Computing in Industry 4.0

Edge computing as a concept comes from networking in which the "edge of the network" refers to the branch offices and other remote installations of an organization. In a manufacturing system, these are the sensors and actuators distributed along the shop floor where data collection is most sparse compared to devices in the cloud. When a mountain of sensor data is sent over to the cloud, hasty computations can also be a consequence. Thus, the term "fog computing" was also coined to refer to "edge devices getting overwhelmed by too much or too fast data." Nevertheless, the number of IoT and IIoT devices is still increasing. With nearly 10 billion IoT devices already active, the number of Internet-connected things overtook the total number of people on the planet. With increased technological advancement, the growth of the Internet of Everything (IoE), which includes people, things, data, and processes, is accelerated.

With the latter problems in mind, some data scientists are of the consensus that the era of edge computing is upon us. Measuring the anticipated growth, a global market report on edge computing concluded that edge devices have more than 6 billion installed units; this therefore produces a global annual data output of over 175 zettabytes! The addition of edge computing to the vast array of cloud computing and fog computing was thus called an "extensive polygenetic cloud model." Among various complementary definitions: "Edge computing has grown considerably in popularity and size. As a complex and structured system, edge computing concepts and terms are not yet fully established in the technical community. Additionally, the term edge computing is often used as an all-inclusive name for the field of edge computing, including all types of applications and systems that involve the deployment of edge devices in a network. Usually, this lack of specific terms has caused much ambiguity in communication." The same edge computing technological landscape map has been attempted by several confederated organizations since then.

3. Real-Time Quality Control in Manufacturing

Quality control in manufacturing is pivotal to ensuring that final products meet the design specifications and expectations of customers. Traditionally, manufacturers rely on statistical process control and visual inspection to detect process faults. However, with an increasing volume of data from production, automation, and improvement of the accuracy, reliability, and speed of fault detection have become pressing needs. Detection of faults as close to the root cause as possible is critical to avoid producing nonconforming products further down the line.

Recent years have seen the increasing adoption of deep learning for visual inspection in manufacturing. A common approach to applying machine learning to quality control starts by first training a neural network for image classification using training data for different types of defects. Defects are then manually labeled or annotated in a large number of images. An approach for fault detection is the use of deep autoencoders for unsupervised anomaly detection. Within deep learning, convolutional neural networks are widely used to extract features from image data and can be used for feature-based anomaly detection. The CNN model is first trained on images without defects. Once the model has learned which features represent 'normal' images, it is expected that it will not perform well on images with defects. An image with a defect may be classified as an anomaly and thereby detected.

Successfully implementing an AI-based quality assurance solution in manufacturing is, however, non-trivial. Factors such as model constancy, robustness, real-time ability to integrate into the production line, and the labor-intensive model tuning process limit the widely adopted applications. We illustrate current research on AI-based fault detection for quality assurance on the shop floor. The selected studies include deep learning, edge computing, and explainable AI technologies. We discuss the merits of these technologies and advocate future research topics that are worth further study.

Fig 3 : Real-World Examples of Digital Manufacturing in Action

3.1. Challenges in Traditional Quality Control Methods

Inspected objects may exhibit intricate microstructures that are crucial for the guarantee of functionality. Obtaining full microstructural details is mandatory for in-depth inspection of certain devices. In many established fields of manufacturing, such as in MEMS, NEMS, and micro-optics, control and inspection of the microstructure are as important as the dimensional measurement of the objects. Over the last three decades, the semiconductor industry has been growing at a rapid pace. This rapid growth in the semiconductor industry is mainly attributed to the constant push for miniaturization of semiconductor devices that provide higher functionality to their applications at reduced costs. However, the increasing complexity of the intricate structure of advanced application-specific integrated circuits makes characterization and qualification increasingly difficult, time-consuming, and costly, as innovations in the superficial appearance of objects do not follow the complexity of these objects' internal structures.

Defect influence assessment and qualification have largely lagged behind the procurement of conventional semiconductor products. Although the challenges faced in adaptive fault diagnosis and maintainability are similar at a higher level of abstraction, they can be performed using specialized electrical test structures such as parametric testing and built-in self-test schemes. These can be automated to assess the placement and performance of specific process design components. However, to guarantee the robustness of critical sensors when a certain industrial plant is operating, it is necessary to assure quality by employing micromechanical metrology and/or visual micro inspection techniques. Critical sensors are prone to being twisted, bent, scratched, or abraded during use. These mechanical deformations can have serious negative effects on the required characteristics and performance guarantee. With the approach suggested in the present work, mechanical deformations below a micrometer can be assessed online by microvisual inspection of the embedded sensors.

3.2. Benefits and Applications of Real-Time Quality Control

In summary, real-time quality control can contribute to reduced costs, optimized production processes, and most importantly, high-quality and outstanding products. Among these, reduced costs are mostly achieved through improved production methods, such as less time, lower energy, and more effective resource utility. Optimized processes can lead to improved quality, such as higher accuracy, better timing of inspections, better-informed decision support, and cost-sharing between revenue and costs. However, the list of benefits can go on. Particularly, real-time quality control can help with label detection, digital watermarks, material identities, and product blockchains. It will also be an important piece in the puzzle of digital transformation when the prediction of production waste due to potential issues has become an empty place where the answer should be definitive. There will be no superior quality or waste of understanding or compromise when everything is under control.

Surface Defect Detection ACs often occur as a result of manufacturing processes. In the AI era, edge computing can be used to make the efficient collection of data more automated. Convolutional neural networks can be used to find deep learning-based methods such as surface defect detection. Efficient data collection will provide automation in data logging, and it is critical for model training and the interpretation of real-world data. After the post-processing stage of the detection is performed, the result is carefully examined, and the critical data sync quality control finds specifications.

$$M(t) = \mathcal{P}(\delta R(t), \mathcal{D}(t))$$

$M(t)$ = Maintenance decision at time t

$\delta R(t)$ = Deviation in system performance at time t

$\mathcal{D}(t)$ = Data from edge devices at time t

Equation 2 : Predictive Maintenance (AI + Edge Computing)

4. Predictive Maintenance in Manufacturing

Predictive maintenance (PdM) is not a new concept in the domain of smart manufacturing; it simply indicates that a condition-based maintenance approach is adopted. What is different with Industry 4.0 is that, with the use of low-cost sensors, big data processing tools, and modern AI models, it now becomes feasible to assess the condition of an organic system and the need for maintenance, thereby avoiding machinery failures. When failures are avoided, production downtime is greatly decreased and maintenance costs are drastically reduced.

For manufacturers who continue to rely on the traditional force-based approach, equipment breakdown may result from settings made by a mechanic after hearing a strange sound. This is a real scenario where costs continue to escalate. By utilizing insulating sound sensors and monitoring for sound changes within a time slice, one could easily predict an abnormal machine running situation.

Predictive maintenance systems can prevent downtime crises, but such systems are not free either. What if they need manual checking—valuable engineer hours? In realistic scenarios, the operating patterns of a facility usually are not continuous, making it difficult to maintain normal use of traditional wireless networked and AI model-dependent maintenance tools that rely on heavy computing resources and/or the availability of expensive and limited bandwidth.

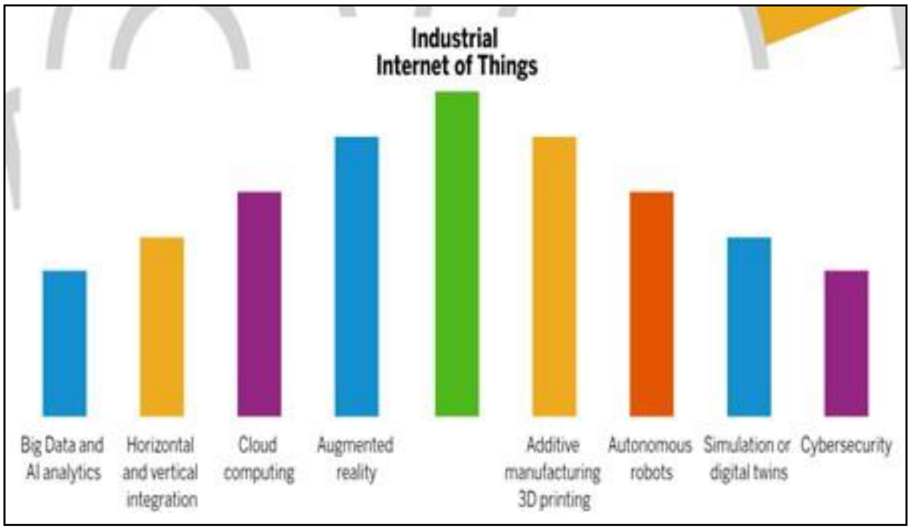

Fig 4 : Industry 4.0: The Future of Manufacturing

4.1. Concept and Importance of Predictive Maintenance

In the manufacturing context, equipment such as the press, stamping, welding robots, food processing equipment, and equipment used in the oil and gas sector need frequent repairs and rest for proper operation. These kinds of equipment frequently encounter the problems of breakdowns, factory shutdowns, and lost profits. Although today's manufacturers understand the importance of equipment maintenance, they still don't know when to perform it. They still use traditional maintenance methods like corrective and preventive maintenance that lead to the above-outlined challenges. Predictive maintenance is a new term that is more capable of decreasing the costs, labor, and maintenance time of equipment. The predictive maintenance method uses both mathematics and computer data that keep records of past interactions of equipment so that we can understand the failure patterns of the equipment and can design the maintenance accordingly. In this paper, we analyze various existing methods of predictive maintenance. Predictive maintenance is the most effective tool currently being utilized for condition monitoring and preserving the present state of the various equipment used in different industry sectors. It is anticipated that implementing improvements to manufacturing technology is expected to decrease the failure occurrence, ensuring a more reliable process. The effectiveness of this approach is demonstrated with two case applications based on actual industry use cases from different sectors: automotive and aerospace. As a result of implementing the predictive maintenance approach, both these industry sectors can increase uptime and spare part planning to ensure customer interest.

4.2. Implementation of Predictive Maintenance in Industry 4.0

One way to implement predictive maintenance is by using vibration analysis to detect the condition of the machine. There are a few methods used for detecting the condition of the machine based on this approach. The features of the vibration signals from the machines are the main characteristics involved in the detection. To analyze the condition of machines using feature extraction from the vibration signals, a few methods exist, such as time domain, frequency domain, and time-frequency domain analysis.

Time domain features to analyze the non-periodic and intermittent characteristics include the signal mean, root mean square, standard deviation of the signal, skewness of the signal, and kurtosis. These features differentiate the abnormalities of the machine, such as shaft misalignment, lubrication level, or imbalance. The features of the vibration signal extracted from the time domain will be applied to statistical and mathematical calculations. The vibration signal can be converted into the frequency domain and then processed by an algorithm, which can convert a time series into its frequency components. The vibration feature component of the signal is displayed as a spectrum over the frequency domain. The frequencies offer benefits in terms of simplicity, speed, and ease of communication to identify the state of the machine. The frequency domain features, such as peak-to-peak displacement, root mean square speed, velocity, and power spectral density, are involved in categorizing fault detection, bearing defects, gear systems, or component faults.

5. Case Studies and Applications

The complexity of the processes in manufacturing demands the flexibility of computing resources. Deep learning models have been developed for quality inspection, yet most approaches perform the learning task offline, which demands a lot of time and computing resources. This approach can be particularly impractical for applications of industrial interest, for which the deep learning model has to be retrained frequently or semi-continuously, due to changes in the production line setup, all the different product types, or the aging of the equipment. In this research, a real-time vision-based quality control system employing a deep learning model for nut quality classification was developed. The learning of the model was performed at the edge, thus allowing straightforward online updates and adjustment of the model to the current state of nut production. Consequently, a data flow required for developing, testing, and deploying machine learning models at the edge is proposed. The data flow is applied to the real-time vision-based quality control system for the detection and separation of hazelnut plants from weeds in the challenging outdoor environment and a real-time vision-based quality control system for nut quality classification. Additionally, two models that demand a lot of computing resources, prototypical neural networks for use on mobile devices and tiny YOLO, were quantized and pruned and then deployed on different microcontrollers so that the potential of edge computing fully supports the developed models. The results show that the medium-complexity deep learning models perform exceptionally well when applied at the edge; the quantization and pruning are crucial steps that reduce the size and improve the speed performance of the models to the desired level.

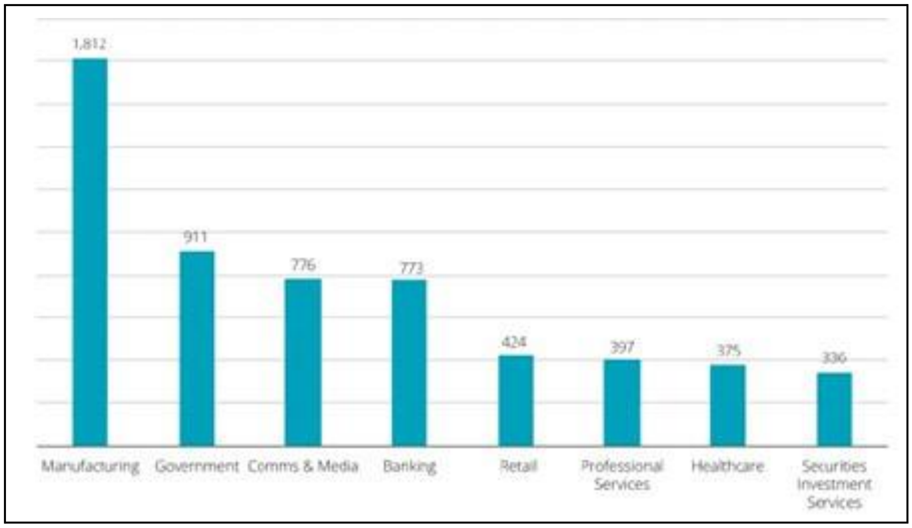

Fig 5 : AI in Manufacturing

5.1. Real-World Examples of Resilient Manufacturing Implementations

In the following, we present some examples of research approaches to increase the resilience of manufacturing systems. Focuses on developing an AI-driven manufacturing quality inspection system with affordances for manufacturing workers. Leverage edge computing in a practical predictive maintenance scenario. Present a system for distributed computing using olfactory sensors for early detection of line stop causes during automotive production. Exploit cloud-based multi-integration of operational and maintenance aspects. Propose a model for integrating assembly time estimation into a design process. In their Cyber-Physical Approach project, can detect and react to problems before they affect the process. Hosting CNC legacy machines in an IoT platform, have their diagnostic analysis ready when building upon their framework, as do for their IoT cross-layer monitoring for the automotive industry.

Present their approaches to 5G and task offloading in a workflow, as well as a framework for a fault-tolerant adaptive cyber-physical system. Deal with variability sources in production systems such as sensor errors, outliers, or failures, in response to the real-time response requirements. Propose an approach to handle the synchronization of sensor data in the context of multiparametric quality assurance, leveraging machine learning algorithms for in-line product quality assessments. Propose a framework and prototype for anomaly detection and root cause analysis of HVAC systems, using detectors and an AI-driven digital twin. Finally, propose an inter-cloud job plugin that extends solutions with a simulator and a multi-objective super-scheduler.

$$R(t) = g(A(t), S(t), D(t), P(t))$$

$R(t)$ = Resilience at time t

$A(t)$ = AI insights

$S(t)$ = Supply chain state at time t

$D(t)$ = Demand fluctuation

$P(t)$ = Production adjustments

Equation 3 : Supply Chain Resilience (AI-based)

5.2. Success Stories in AI-Driven Quality Control and Predictive Maintenance

In this section, we present two best practice cases of employing pooled domain expertise to develop advanced AI systems for smart quality control and predictive maintenance, respectively. We first provide an overview of the companies and the real-world business and technological challenges that triggered their respective interest in applied research. Then, we present the employed methodology and discuss the developed AI-enabled solutions for the identified challenges across the design of experiments, machine learning, and working applications to real-time camera data as well as real-world scenarios solved and business impact achieved. Finally, we critically evaluate the results of both initiatives and discuss possible ethical implications before we close the chapter with a summary and an outlook on future work.

To validate our technology, we set up a manual test bed in a camera observation facility and produced very dark or very bright products that cannot be inspected by the human eye. This makes it impossible for the factory operators to rely on their visual senses to maintain production quality. We design and process several specific experiments with actual use cases from the domain of customers in the area of non-food inspection, such as print inspection or cracking inspection for production glass sheets. For the print inspection use case, we apply classifiers with a size of 37 megapixels in each image.

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