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Integrating Edge AI in Smart Factories: A Case Study from the Paint Manufacturing Industry

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Abstract: ***The rapid advancements in edge artificial intelligence (AI) technology, also known as edge computing, have made the use of AI computation on local smart edge devices for in-factory automated decision-making a reality. Paint manufacturing is a capital-intensive industry where process parameters must be strictly controlled, a long-time process for standard product progression, and timing and quality deviations are intolerable for some customized products. To produce money-backed customized products, the manufacturing process data must be assured to show perfect traceability. These add a new phase to the AI-powered smart factory literature. AI-powered smart edge devices, such as intelligent VFOs, AI-based cameras, and industrial PCs, are designed to work in a fan-less environment and are easily integrated with existing old machines. The integration of smart edge devices will convert smart factories into factories with smart machines, enabling data coverage for all workstations while minimizing loitering time over operating machines. Smart edge devices can upload the AI inference results to a mental cloud platform for real-time monitoring. This Edge AI-enabled mental cloud brings a brand-new computing topology for industrial big data. It has the advantages of both national public cloud and local industrial equipment. The introduction of Edge AI dramatically saves bandwidth and ensures data privacy, allowing for affordable and compliant solutions for industrial factories when data compliance issues are brought to the forefront. Case studies show that integrated Edge AI-enabled smart factories can realize a smoke-free production line at low costs and provide low-latency product quality predictions under acceptable accuracy, which reshapes the operation of paint manufacturing sites and provides new opportunities for the smart chemical industry.***

Keywords: Edge AI in Manufacturing, Smart Factory Automation, AI at the Edge, Industrial Edge Computing, Paint Manufacturing 4.0, Real-Time AI Processing, Edge Analytics for Industry, AI-Driven Quality Control, Smart Sensors in Production, Factory Floor Intelligence, Predictive Maintenance with Edge AI, Edge-to-Cloud Integration, Industrial IoT and AI, Decentralized AI Systems, Edge Computing Use Case in Paint Industry

1. Introduction

In the new era of the industrial revolution, manufacturers of all sizes are adopting digitalization models like Industry 4.0. However, most manufacturers cannot afford to adopt these smart manufacturing technologies—especially small- and medium-sized manufacturers. Since the COVID-19 outbreak, the necessity for smart manufacturing has exploded in an unprecedented manner, as the lack of contingency plans has resulted in substantial losses to both manufacturers and unaffected supply chains. Falling behind in the adoption of smart technologies and systems will potentially eliminate companies from existence. Small- and medium-sized manufacturers account for the majority of manufacturing capabilities, and thus, need to be completely supported to expand intelligent manufacturing capabilities. Edge-based AI (artificial intelligence), which is affordable, scalable, accessible, and portable, can be a practical solution for manufacturing in desperate need of smarter technology. A reference design of Edge AI was comprehensively developed in this research, aiming to illustrate the entire exploration and implementation process so that similar types of manufacturers can follow. The affordability, accessibility, scalability, and portability of these technologies are addressed for small- and medium-sized manufacturers needing to improve product quality.

Manufacturers globally face challenges like maintaining a competitive edge at local and international levels, keeping up with evolving customer demands and competitive pressures, and ensuring a sustainable closed-loop process that can save costs. To address these challenges effectively, the manufacturing industry is evolving into smaller, more adaptive, and agile factories, utilizing increased connectivity and advanced technologies for smarter asset utilization and efficient factory management. Competitive pressures continue to drive manufacturers to lower costs and increase productivity through asset optimization, as focusing on electricity conservation alone remains insufficient. Despite significantly improved energy usage and production cycle efficiency, greater resource efficiencies need to be achieved through holistic efficiency across the entire supply chain. To meet customer needs more agiley, mass customization and a smart factory model will need to be adopted. With the use of information technologies, smart factories allow improved visibility, traceability, adaptability, and sustainability of the manufacturing process from the design phase throughout the product life cycle. Smart factories entail highly connected and intelligent machines, resources, and manufacturing processes, along with automated process optimization and control.

However, existing smart factories are typically associated with high costs and complexity, adopting space-occupying machinery and heavy management software. Small- and medium-sized manufacturers face hurdles transitioning to smart factories, as the benefits are outweighed by costs and complexity. Understanding the performance of poorly connected, low intelligence manufacturing facilities is crucial prior to any upgrade decisions, which is impeded by inadequate understanding tools and advanced performance monitoring technologies. Edge AI focuses on deploying analytical models on edge devices, enabling low-cost, low-complexity, and privacy-protecting analytics without extensive changes and investments in existing facilities.

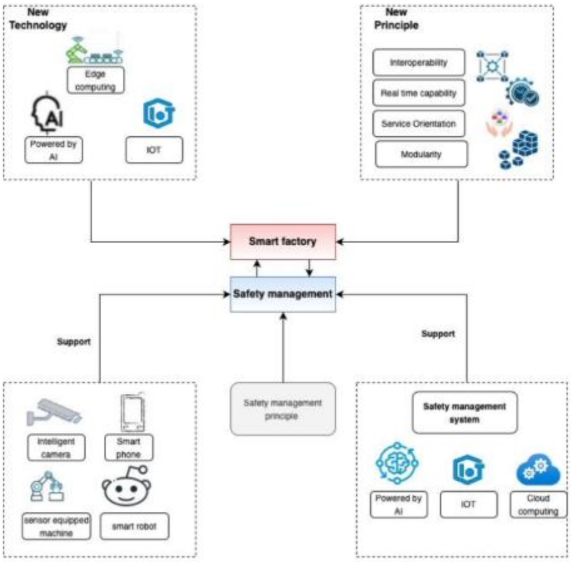

Figure 1: The Role of Edge AI in Smart Factories and Industries

1.1 Research Design

As a pivotal part of Industry 4.0, Smart Manufacturing has received high regard in academia and industry in recent years. As an important technology of Smart Manufacturing, Artificial Intelligence (AI) is integrated into the traditional manufacturing process to make it smarter. Opportunities are created for factories to improve the traditional systems with AI and enhance smarter systems, explore the applicability of edge computing with AI for on-premise computing to promote intelligence within factories. With the purpose of enriching and facilitating wider use of AI in Smart Manufacturing, this study investigates AI deployment within a factory, represents a case study within a paint manufacture factory, and introduces an Edge AI model as a typical AI deployment framework for smart applications. This framework consists of R&D, model inference and training, and data upload and refinement. To demonstrate the applicability, a case of product color matching is used and implemented within the factory in consideration of uniqueness. The AI implementation framework is evaluated from six aspects, and shows great applicability within different factories.

Flexibility and efficiency are two critical factors for production systems. Lean manufacturing, one of the best-known philosophies for improving production performance as well as manufacturing knowledge, was originally designed for discrete manufacturing and assembly systems in the 1990s. Recently, it has been adjusted to hybrid models and industries, e.g. Aerospace manufacturing. Meanwhile, advanced manufacturing extends the field for that enhancement with cyber-physical systems and internet of things technologies. These technologies are adopted and emphasized to improve monitoring and visualization for better time-aware production. However, considering the large variation of tasks, such flexibility cannot be achieved without proper systems and methods, which makes an extension on productivity from lean to discrete dynamic job shop difficult. Furthermore, compared with traditional manufacturing, mining production is less researched especially on flexible job shop. Few research works on productivity improvement are still focusing on either model-free learning methods with no active intervention or model-based methods on one approach at a time.

Equ 1: Product Substitution Recommendation.

$$S_{ij} = \cos(\vec{p}_i, \vec{p}_j) \cdot A_{ij}$$

- $\vec{p}$: Product embedding
- A_{ij}: Availability flag

2. Background of Smart Factories

Smart factories, as evolving production paradigms, utilize advanced information and communication technology (ICT) frameworks and automated production equipment to achieve autonomous production. They enable the diagnosis, prediction, control, and optimization of production processes while establishing a bidirectional cyber-physical connection between the physical world and the digital world. Smart factories are considered one of the core representatives of Industry 4.0 and represent a new trend defined by the interaction of a cyber-physical system (CPS), the Internet of Things (IoT), and the Internet of Services (IoS). Another interpretation of smart factories is fully connected and flexible manufacturing systems that can use machinery, storage systems, and computer control to optimize production.

A growing consensus is that changes in the economy will be driven not only by augmented underlying connectivity but by the idea of digitization in production systems and practices. Smart manufacturing technologies consist of new approaches and applications of advanced manufacturing technologies that provide enhanced performance to manufacturing systems and processes. Key technologies include the industrial Internet of Things (IoT), cyber-physical systems (CPS), cloud computing, big data, and artificial intelligence (AI). In a smart factory, all manufacturing assets have the capability to measure, analyze, and communicate data from them.

On one hand, unprecedented opportunities are afforded by the emergence of AI. For example, AI-based computational intelligence allows manufacturing systems to perceive their environment in the presence of uncertainty through learning and reasoning from past experience. For example, using AI for diagnosis, prognosis, and health management combined with industry 4.0 technologies can offer factories predictive maintenance capabilities. Reinforcement learning, as an important category of AI, was pioneered for training agents to make decisions that maximize cumulative rewards. Although proven in specific areas, it remains difficult to implement in manufacturing due to the complexity of creating an accurate model of the number of actions, states, and transition probability functions relative to the reward. On the other hand, the combination of operational technology (OT) and information technology (IT) provided the foundation for the emergence of intelligent tools and equipment connected in a larger network.

2.1 Definition and Characteristics

The state-of-the-art technologies adopted in customized smart factories raise concerns from enterprise-level integration and cooperation perspective. The lack of standardization and heterogeneous enterprises in manufacturing ecosystem complicate the application of these technologies. In addition, an AI-driven loyalty system that offers value-added service has hardly been investigated. Therefore, a conceptual architecture of an AI-driven customized smart factory and a customer-loyalty-enhancement procedure including the corresponding strategies and tactics are developed. Customization novelties are presented, including task reallocation between intelligent agents and AI model transferability based on membership differentiation. The characteristics of the cognitive economy pose challenges of how to define loyalty, and how to utilize big data for loyalty creation. Concepts of loyalty, customer segmentation, and AI-enabled loyalty system are articulated and advanced. The steps of constructing a customer-loyalty-enhancement loyalty system are proposed. A multi-granularity usage-based method for acquiring aware loyalty and a view-based satisfaction-driven method for acquiring unawared loyalty are proposed. The validity of observed tactics is verified using AI technology-enabled numerical simulations.

The modern painting process includes multi-stage treatment of various products and surfaces. The functions and data generated in each treatment stage form the overall integrated manufacturing process of the painting production line. The processes in each operation model can be defined as a smart factory that can be dispersed and integrated. AI, as an important tool for manufacturing decision-making, has empowered the painting process to be a self-perception, operations optimization, dynamic indispensable production mode. This process, as a customized smart coating factory, will build a multi-agent cooperation mechanism to integrate the optimized capacity and economy of share, newly developed and resource-constrained painting line. Many more challenges of newly breakdown tasks will need AI-enabled agents to expert in customized painting preparation. AI will be developed to extract modeling knowledge from SCADA data of the smart painter or the robotic paint spray and coating equipment, and new perception devices. In the painting measurement and fault diagnosis, modeling data-preparation, processing and testing will need to cooperate with the vocational conversion of defect-detection tools. AI, as a data-driven to modeling approach, is facing challenges of which dataset to use and model transferability when facing less training data in defect-detection cases. AI-enabled agents will be developed to target these challenges and to collaborate with programming tools.

2.2 Historical Evolution

Manufacturers have been striving towards a flexible and resilient ideation-manufacturing distribution with digital networks throughout the developments of electric, mechanical, automated, data-driven, and intelligence ones. The traditional production paradigm of large batch production cannot fundamentally be reengineered to offer flexibility and resilience towards satisfying the requirements of individual customers. Catalyzed by the Fourth Industrial Revolution (Industry 4.0), a new generation of smart factories is emerging with stronger flexibility and resilience. On one hand, the intelligent surfaces of product, process, and machine enable unprecedented capabilities of self-perception, data-analytics-enabled operations optimization, and machine-intensive dynamic reconfiguration. On the other hand, reconfigurable production systems with digitally-twin-based virtual simulations, customizable and more precise prototyping methods allow the supporting of new multi-variety and small-batch customized production. Industrial Artificial Intelligence (AI) technologies are expected to enable higher value added manufacturing by accelerating the merging and epistemic-ization of manufacturing and information communication technologies, which is termed as "Smart Factory" and is commonly referred to as Industry 4.0. According to the Industry 4.0 framework, the characteristics of a customized smart factory should include: self-perception; data-analytic-enabled operations optimization; machine-intensive dynamic reconfiguration; and intelligent decentralized decision making. Such AI technologies should allow manufacturing systems to perceive the environment, adapt to the external needs, extract the processing knowledge from data, collaborate, share knowledge, and make decisions. The manufacturing operations of most small to medium-sized manufacturers are bespoke, and usually performed through manual or heuristic-based processes. The rapid evolution of this manufacturing paradigm is driving an urgent need to create useful tools for its stakeholders, namely, small to medium-sized manufacturers and their engineers. A consumer visualization tool based on a simplified visual programming environment is developed for the aforementioned purpose. It offers an end-to-end data model development workflow where a diverse family of data models is created from pre-existing business system data and re-used readily to address multi-faceted workflows. The design is focused on low-cost, easy-to-use, and easily scalable factors, which are key to the feasible adoption of the smart manufacturing ecosystem. Real-world experiments and manned demonstrations with small/medium-sized manufacturers are provided to validate the usability of the proposed tool.

2.3 Current Trends

The rise of the Internet of Things (IoT) and Wireless Sensor Networks (WSNs) has transformed smart factories and industries towards actual implementation of Industry 4.0. A wide range of new mechanisms and applications for Industry 4.0 have emerged, leading to the second decade of intelligent manufacturing, known as SI 4.0. AIoT, Enterprises-level Big Data, Digital Twins, and Metaverse Technology have become the central focus to achieve inclusive, holistic, and sustainable intelligent factories. AI technology can faithfully replicate reality in the virtual world by feeding real-time data inputs. The fusion of three technologies, i.e., edge computing, augmented reality (AR), and AI, is addressing the challenge of real-time analysis, decision-making, and monitoring in manufacturing processes. During the digital transformation of manufacturing enterprises, smart edges of affordability become the enabler for ubiquitous intelligence at the shop floor level, with consideration of cost-effectiveness, accessibility, scalability, flexibility, and interoperability.

The painting workshop is characterized by the vast and repetitive job-shop operations. Color matching, paint preparation, intelligent paint injection, and real-time monitoring are key aspects to pursue sustainable integrated intelligent smart factories. Each type of smart application embraces extensive AI deep-learning based edge approach. A batch of digital twins self-replicated from painting lines is built up for cyber-physical systems monitoring and optimization. A comprehensive industrial metaverse is implemented for holistic monitoring and visualization, optimization and simulation, and collaborative design and construction of engineering works. The paint manufacturing industry business processes are digitized into the systems of electronic production order management, paint-color matching, and paint preparation resource optimization. An integrated big-data infrastructure based on the cloud and edge is built up for auxiliary analytics and insights. The paint-shop-floor experiment and implementation validate the effectiveness and scalability of the integrated intelligent approach.

3. Overview of Edge AI

As a leading segmentation technology, edge artificial intelligence (Edge AI) incorporates AI capabilities on edge devices to analyze data locally. This approach answers the growing demand for machine learning processors for smart devices that lead to a quicker response, increased privacy, and reduced bandwidth usage. This capability is supported by high computing chips like Graphics Processing Units (GPUs), Tensor Processing Units (TPUs), and Field-Programmable Gate Arrays (FPGAs). Owing to the convergence of AI and edge computing, Edge AI has become increasingly popular in numerous applications, particularly in manufacturing and processing, such as smart factories. The growth of the significance of Edge AI is linked to the proliferation of industrial automation peculiar to Industry 4.0 (I4.0). Edge analytics platforms and cloud-hosted BI tools are increasingly being adopted in smart factories, as they can interpret the thousands of edge devices and sensors generating terabytes of production data in real-time systems. In addition, AI-enabled edge platforms that can analyze the vast data generated from the factories by AI algorithms and offer intelligent recommendations are also paramount in the application of AI in smart factories.

Manufacturing information systems generate a huge amount of ingested data that need to be analyzed not only for insightful decision-making but also for safety and predictive maintenance. Despite advances in Edge AI enabling on-device analytics in time-sensitive domains, applying these capabilities to manufacturing is still in its infancy. Mobile applications, programmable logic controllers (PLCs), and end-nodes perform data ingestion. These are limited in capability and power due to their design and constrained business necessities.

Wiser manufacturing analytics provides visual analytics in engineering workstations and dashboards; however, it consumes more resources and cannot optimize decision-making. AMD Absolute enables edge analytics for machine learning decisions; however, training data are computed on cloud servers, which can present a privacy threat. Amazon Lookout for Equipment enables Edge AI that analyzes data locally using an aggregate anomaly detection model. Nonetheless, intelligent recommendations cannot be provided to the experts, as the decision-making is not automated, and further domain knowledge is required to detect the root cause. In this regard, the edge AI prototype with dynamic machine learning is developed to provide smart recommendations. This prototype is validated in a case study of the paint manufacturing industry, where over 60,000 paint cans are produced, leading to disorder and defect detection. Automotive painting defects are detected in one single computer vision (CV) model, with recall and precision by a standard lightweight YOLO model of 75% and 77%, respectively. A parallel edge device with model distribution and data fabric is specifically proposed for real-time decision-making.

It aggregates the findings of the CV, cloud computing, and decision tree models and controls the machine accordingly. To the best of the author’s knowledge, this prototype is the first application of edge AI with the capability of smart recommendations in this case study. It goes beyond the limitation of previous manufacturing systems where Edge AI is supported only by light computing and response capabilities, while the recommendations based on aggregated AI findings are automated at the edge level according to manufacturing dynamics.

3.1 Definition of Edge AI

Edge Artificial Intelligence (AI) refers to the application of machine learning algorithms at endpoints–typically on smart sensors and/or edge computers representing the first line of computing in a system or a network. The end systems could be any software or hardware products or services for the Internet of Things (IoT) that have an integral interface and/or engineered boundary through which data can enter or leave. Such capabilities may include, but are not limited to, machines, terminals, end-user equipment, and devices. AI algorithms, by making these systems intelligent, allow them to provide information security and computing efficiency that are more fundamental than what shall be achieved by the underlying network and computing infrastructure. The key idea behind edge AI is to run the AI algorithm on the device or edge computer itself using only local data. This way, the raw data does not have to travel to the cloud, avoiding privacy issues, high latency, and large energy consumption.

Edge computer, a term synonymous with edge server, fog computer, or fog node, refers to computer systems that are located at the edge of a communication network. These computers are situated between a source that generates data, e.g., camera, machine, sensor, and a cloud platform that receives and/or stores this data. Edge computers usually provide a much larger storage and processing capability than what each generating source has. Consequently, these edge computers become potential beneficiaries for running machine learning algorithms on data from one, or often multiple sources.

In this way, the power of AI can be leveraged to the edge of a system or a network, thus enabling the application of edge AI without deploying computationally expensive cloud computers. Edge AI is particularly important for IoT applications since many sensors produce large amounts of data that are difficult to be sent to a cloud for storage, very limited edges have been developed to connected IoT systems, power outage is likely to happen in remote areas, and the concern of user privacy could arise.

3.2 Benefits of Edge AI in Manufacturing

Most of the industry considers intelligent manufacturing to be a great opportunity for transformation, driven by the automation and sensible connection between the manufacturing intelligent and traditional productions. However, over the last years, the integration of IT and OT (Operational Technology) has urged the necessity of intelligence, and now is the time for mass imposition of information technology and network modernization on industrial sites, during which the intelligent analysis of large data builds value for manufacturing intelligence. The internet of things (IoT) at the edge of industrial sites brings resolutions for sweeping data.

However, early implementations did not consider data, and huge amounts of invalid data are continually being uploaded to the cloud. Industrial data without context or intelligence leads to problems of data ownership and cyber security. Therefore, how to provide a suitable deployment scheme for the effective implementation of Edge AI integrated with smart factories is an important issue to be solved.

Figure 2: Benefits of Edge AI in Manufacturing

Currently, most cloud analytic systems do not support edges, as the cloud deployment architecture itself is already of an edge nature and considered for plant-level integration. Meanwhile, even if appropriate cloud systems are deployed to incorporate the comprehensive discrete aspects of factories, the massive amount of sampled logistics data uploaded to the factory-level system would burden the factory-level network. Moreover, external use of the data will bring out concerns about data access and privacy. Opposed to cloud-only systems, on-edge implementations of industrial data, required data models should be predefined in a way that simplifies acquisition and improves analytics. In the manufacturing practice, edge-type deployments of geographic information systems (GIS) and data orchestration banks are common. Alternatively, edge-type systems will be limited to topologically resilient yet fully captured sites.

3.3 Challenges in Implementation

As smart factories undergo rapid transformation due to advanced technologies, this research explores how smart factory technology affects productivity in paint manufacturing. Despite being a high-tech industry, many paint manufacturers still use traditional production processes. The adoption of advanced technologies by smart factories to realize digitization, wireless connectivity, and AI-based analysis, however, lacks thorough exploration in the literature. When smart factory technologies were introduced into paint-production plants, slow adoption resulted, due to both social and technological challenges. Dynamic, complex, and uncertain manufacturing processes led to limited practical data availability. Smart factory technologies, suitable for controlled and easy-to-automate processes, were ineffective in volatile environments. New AI models must be developed to enable successful model building. Fundamental learning on this topic needs to be conducted during the model development phase, resulting in a time-consuming learning process. The difficulty of implementation and value creation results from a lack of AI expertise. Research on integration technologies is scarce, and existing solutions focus on manufacturing parameters. Technologies are still in a stage of conceptual models, or laboratory and small-scale tests. In fast-decaying environments, existing models have limited practical value and adaptation is costly. Further development and integration of even the most sophisticated AI tools are required to focus on the most promising areas in practice. Most paint manufacturers are hesitant about adopting advanced technologies, resulting in unawareness of possible use cases and an outdated strategic frontier.

Edge AI adoption accelerated where lower edge AI maturity scores were reported. On the pipe level, both edge computing and edge AI must be implemented to enable fast data collection, processing, and acting in a smart way. Edge intelligence promotes timely decision-making based on manufactured good quality feedback in complex environments. In the cloud layer, compatible edge devices are required to support enough edge-aware edge inference together with robust edge-cloud co-training. The front-end deep learning model must also be more dynamic in learning new information and reducing the uncertainty of maintenance prediction and product quality results. The change of data is inherent, and the datacenter can reengineer and build an updated model every time a data drift is observed on the smart factory side. The use of the most generalizable model rather than a specific machine model usually results in a more effective inference with reasonable accuracy.

4. The Paint Manufacturing Industry

In the last part of the 20th century, the application of automation began in the factory scene, bringing a paradigm shift of productivity improvement to the manufacturing industry. Thanks to the maturity of Internet-of-Things (IoT), early in the 21st century, the Internet was adopted in factories, and collective intelligence and big data became possible, paving the way for the fourth industrial revolution, which aimed to overcome the limitations of automation. Intelligent machines were developed to prioritize data science and autonomy over driven automation in factories, resulting in an overwhelming gap from heterogeneous commodities, while existing factories with full automation but no intelligence were stuck in the bottleneck of productivity. Therefore, Enterprise 4.0 transformed the vision of the future-era factory into a smart one, an essential part of which is an intelligent robot.

Delegated by IoT and Artificial Intelligence (AI), smart factories are expected to perceive surrounding environments with heterogeneous sensing & acting components, while AI-driven robots are anticipated to comprehend a variable task with less supervision and capable of collaborative working with other agents, although such futuristic machines are still in the research phase. Directed acyclic graph hatching has been proven to be a promising approach to generating feasible paths for mobile pickers; however, in the real world, the path quality needs fine-tuning due to numerous interfering factors, for instance, near-infrared spectrophotometry, to eliminate shadows and color shift caused by items moving along the conveyor belt which had not been considered in earlier planning.

Moreover, there exist extensive and intensive batch regulating conveyor systems in existing factories. In the traditional route design, paths are manually tuned under point-to-point mapping to fulfill product-specific batch picking when factory layouts are planned, while macroscopic via waypoints are designed for path searching across their schedule during runtime. Initially, clues are drawn from kinematic motion planning solutions, so the path design problem is transformed into one where rough globally geometry-desirable optimizations are globally done, and Rodriguez and McClamroch theory is introduced to filter feasible paths and to tune the planning gait of mobile pickers.

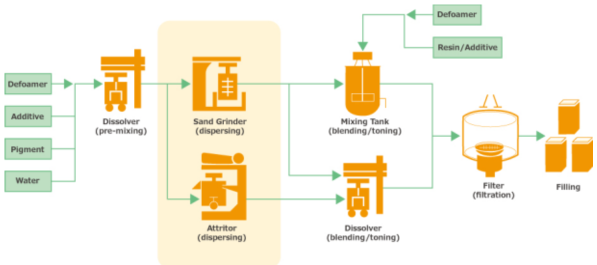

Figure 3: The Paint Manufacturing Industry

4.1 Industry Overview

Manufacturing is an essential component of the global economy and has expanded with the growth of new, innovative technologies. Manufacturing technology will increase productivity in the production of goods, which is essential for industrial growth and a country's economy. Manufacturers are now producing goods at a much faster rate and lower cost due to the introduction of automated manufacturing processes. Manufacturing involves the creation of commodities, equipment, and goods via human labour or machinery, which can include food processing, textile production, and automobile construction. Smart factories are an essential part of Industry 4.0, and the introduction of Artificial Intelligence (AI) into manufacturing and industries will help improve the decision-making processes and manufacturing processes based on data. The Paint Manufacturing Industry is a resource demanding industry, and this paper will focus on Edge AI integration within the Smart Factory of a Paint Manufacturing Industry. In the paint manufacturing industry, the production process uses a lot of resources in the form of water, energy, and raw materials which require close monitoring. Moreover, defect detection is vital for the manufacturer to remain competent in the ever-changing market. Finally, the paint manufacturing industry is labour intensive, with most processes performed individually by local operators without an intelligent input. The approach is a case study of Edge AI Deployment and AI Quality Inspection Model Maintenance for a paint manufacturing industry that looks beyond ML model performance at deployment, addressing broader AI system robustness and integration challenges in an industrial context, covering (i) Edge AI deployment of multi-instance object detection model at the manufacture edge with 24/7 inference, (ii) domain adaptation techniques applied to address concept drift during closed-loop machine learning model operation in factories, and (iii) integration of AI solutions with an existing smart factory monitoring system and visualisation dashboard development for operator acceptance of AI quality inspection outputs.

4.2 Specific Challenges Faced

It has digital challenges and opportunities that exist in a paint manufacturing factory. The factory's metal parts needs to make a connection with the digital world and its automated pieces of equipment for a good AI inspection service. Edge AI devices are needed to be installed on machines, and they have a challenging requirement for seamless integration. The smart paint manufacturing factory has no supporting technology to integrate Edge AI in existing machines. AI systems have industrial job challenges of less influential workforce to obtain labeled data. Edge AI model training challenges are to use a general AI model with limited labeling datasets. Edge AI inspection challenges are high speed and resolution of a paint spray inspection job. It has a lack of roll-out decision support for application systems.

Challenges for Smart Paint Manufacturers to Integrate Edge AI in Factories. The smart paint factory has a set of automated machines, with most of them (>50%) play a role in spray paint and curing. The centralized production execution system already obtains production plan data, online production operation for each machine, and work-in-process (WIP) status. Spray paint machines are the focus of this case study to precisely connect with AI inspection systems. Edge AI inspection needs to embrace machine digital challenges and opportunities. First, the existing machines are from various suppliers, and only basic communication via RS-232 is available. The paint production requires high-speed movement, leading to motion blur in images. Connectivity, bandwidth, and latencies readily introduce jitter, leading to intermittent dropouts. Residual dust on the conveyor directly considers failed inspection. Thus, complex issues arise to digitalize the machines for AI. Second, the paint mostly comes from powder material, needing to dissolve it for broad paint quality control. This controlling is via precise dosing raw materials during paint production and controlling the paint dispensing and nozzle during the spray. A defective paint preparation will finally lead to an abnormal spray. The CNCs and robots have in/sufficient sensors for production operation and WIP data collection. Thus, there is a need to collect the process or idle states' monitoring data and rescale analytical capabilities and decision-making power for these legacy passive machines.

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Equ 2: Cost-to-Serve Optimization

$$\min_{x \in X} \sum_{i=1}^{n} (C_i + H_i + T_i)$$

- C_i: Cost of goods
- H_i: Handling cost
- T_i: Transportation cost

4.3. Innovation

Innovation drives productivity improvements, leading to higher quality products and longer product life cycles. However, the rapid development of new products (NPs) creates problems in resource allocation, equipment arrangement, and low utilization of equipment in traditional factories. The introduction of innovative equipment can improve production efficiency, but existing software and communication protocols for control systems are diverse and specific to the equipment manufacturer. Due to the lack of standardization, edge applications cannot be implemented across factories with different equipment. Therefore, the research focuses on painting in the manufacturing industry, particularly on an edge application called Smart Painting Assistant, which is used in an automotive paint manufacturing factory. The goal of Smart Painting Assistant is to utilize existing sensors on robots that perform NP painting and provide operator recommendations through human-robot collaboration. The innovative paint modelling application needs equipment data to make predictions. However, different machines have different communication protocols, and it is difficult to obtain all the data. In the painting applications, it is important to obtain data indicating whether the painting is ongoing, which can be inferred based on the painting time, or the time since the last painting. This time information can be obtained from the robots' internal state machine without the need for a standardized and industrial grade API.

Human-robot collaboration is a key area of research in Industry 4.0. The Smart Painting Assistant has a focus on collaborative work between operators and robots in the case of NP painting. In most literature, a smart assistant focuses on reduced operator workload or accident prevention, which can directly improve the production efficiency. However, for automotive paint manufacturing, the NP painting is responsible for providing accurate painting data and ink control. If a new paint group with a new colour and its relevant painting strategy is introduced, the manufacturer needs to invest a huge amount of resources and time to repaint all the previous components whenever possible. Thus, research needs to focus on improving the accuracy of the paint group and ink control with the assistance of edge applications.

5. Case Study Methodology

This section presents a detailed description of the case study methodology employed in this research study on Edge AI in Smart Factories. The process of the case study is presented, and along with it, how the data has been collected and analysed.

As this study is exploratory in nature, case studies are deemed to be one of the best research strategies when seeking to answer "how" questions or understand why events happen in the context being studied. The multiple case studies help determine the unit of analysis, both at organisation-wide and evidence-source levels, such as the enterprise systems employed in manufacturing. A qualitative approach has been adopted for the study, so that in-depth understanding of Edge AI implementation in smart factories can be gained. In line with this approach, a total of 12 case studies were conducted in paint manufacturing factories and technology companies. All the cases were selected purposively considering prior knowledge, experience, or interest and happen to be involved in Edge AI enterprise system implementation. The key informants who were instrumental in Edge AI smart factory implementation were identified and contacted for interviews, with the aim of collecting rich data and firsthand information about the project, its challenges, implementation process and change strategy adopted. As a wider range of case studies provide better generalisability and replication of outcomes, the number of cases was limited to less than one dozen, so more meticulous documentation could be paid to each depth and detail towards better data analysis.

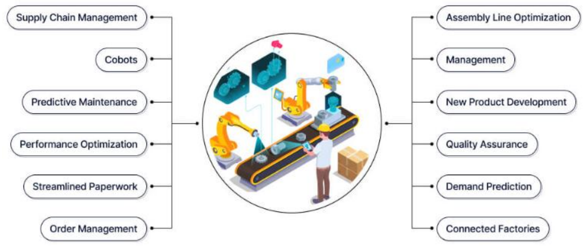

Figure 4: Case study of Edge AI in Smart Factories.

To support the case study research, two research instruments were developed—the protocol and the guidelines. The case study protocol was designed concurrently with advertising the case study to control the data collection and analysis processes. It began with a checklist covering the design of research questions, study instrument design, sampling and selection of research subjects, pre-test and revision, piloting, and documentation of case studies. Following this protocol, a list of candidate cases was first developed, and then companies or design institutes involved in Edge AI implementation were screened and contacted for possible participation in this research. When it was not successful on the client-side, the projects executed internally in software vendors were considered until a satisfactory scope and depth were achieved.

5.1 Research Design

The objective of Integrating Edge AI in Smart Factories is to explore the implementation of Edge AI theory and methodology for smart factories by using the paint manufacturing industry case study. This study is expected to yield high demand and prize in the manufacturing community and new insights to understand intelligent systems, including Edge AI, in smart factories. Given the urgent need for the manufacturing industry to go smart and the importance of Edge AI, a diversified research design with qualitative and quantitative methods is proposed for the in-depth exploration and comprehensive examination of the research subject.

The three main questions are proposed regarding the thorough understanding of the intelligent system (Edge AI) in the context of smart factories in the paint manufacturing industry and the corresponding theoretical modeling after the empirical research. The contribution of the research design is twofold with the theoretical modeling yet not well-known domain (Edge AI in smart factories) and the diversified research design including multi-case study, questionnaire survey and concept modeling.

The research subject on integrating Edge AI in smart factories is theoretically significant in understanding the intelligent system in the context of smart factories, especially paint manufacturing case studies with high demand in the manufacturing community. In the last decade, one of the most extensive paradigm shifts of manufacturing was to go intelligent. The advancement achieved by IT has significantly transformed the manufacturing industry from traditional and automated. Extensive research has investigated the aspect of smart factories. However, a well-defined and comprehensive examination of smart factories with theory modeling to understand this domain is limited. This paper builds a theoretical framework of smart factories to convey an all-around understanding by reviewing the literature and synthesizing the question/answers, functions of the intelligent system (Edge AI and other crucial technologies) in the hot sub-domain of smart factories-paint manufacturing industry.
The rapidly increasing preference for low-paint production (small batch) and customized paint production (high variety) meets challenges on manifold production optimization at the factory level. This research on intelligent production optimization uses Edge AI to present the need for the further understanding of intelligent systems in smart factories. Despite much attention on AI in general, specific modeling of Edge AI in smart factories is still limited and inspiring to a larger community. The paper proposes an agent-based modeling of Edge AI with a paint manufacturing factory as a use case, with the potential to be generalized to other manufacturing scenarios and hence the quality assurance.

5.2 Data Collection Techniques

For edge artificial smart factories, the physical store-and-forward architecture approach is chosen to batch, store, and analyze data via edge or premises AI that also has received a supporting RT and AI framework, which embraces diverse and hybrid systems comprising complex AI components. To improve data diversity, graph neural network (GNN) is also leveraged. For mobile cloud/fog AI or collaborative AI, pre-trained models are scaled up, tailored to factories, and customized to sites, product types, etc. With heterogeneous computing engines, edge AI with a GPU card is used to analyze data frames in a parallel frame-by-frame manner.
The edge RT algorithm is developed for batch tracking, recognition, and ROI proposal/frame extraction, after which operations such as batch tracking and mass recognition are performed on legacy servers. To improve accessibility and user experience and eliminate data and knowledge silos, a structured knowledge graph is developed to connect all knowledge elements with analysis reports, forecasting models, and provenance information, while an agile web-based platform leverages agile CI/CD best practices to integrate edge AI-updated models with a mobile app and an eshop plugin.

Two data collection techniques, namely, data recording and real-time data acquisition technique, are developed in pursuit of the goal of a smart factory. The former reconstructs code lists in the Meta Information Parser-based Scene Graph to tackle sparsity and to enrich the diversity of a code set, which is used to train a recognition model. The latter leverages the concept of generic-scale scene graphs built on top-down graphs to onboard production lines and to design RT plug-in AI applications to understand the product in a simpler and easier manner without coding. Through a mobile-based scene graph sharing manager and a plug-in AI app with embedded global and local explainability of predictions, a robust solution is provided for the field application of cutting-edge AI technologies, particularly in a smart factory, while further efforts require an agnostic retail case implementation.

5.3 Analysis Framework

The study focuses on a paint manufacturer in Finland undergoing digitalization to enhance efficiency, competitiveness, and sustainability. Edge AI's advantages for real-time control in the manufacturing process are connected to productivity results. To understand how Edge AI can support a real-time prognosis of foaming in related processes, the Transformative Innovation Policy framework is used with a transversal analysis of context, applications, and innovation capabilities in the manufacturing ecosystem. Preliminary results demonstrate how Edge AI can support productivity outcomes and identify areas for future research.

The manufacturing industry, primarily the paint industry, faces challenges in controlling process quality as production speeds increase. The implementation of Industry 4.0 solutions has been hampered by the difficulty of utilizing big data. Edge AI offers several advantages for extracting valuable information from extensive data use at the data source. Early implementation efforts regard applications of AI algorithms for digital transformation and productivity improvement of interconnected processes, indicating a paradigm shift for the paint industry.

The focus is placed on a manufacturing and paint manufacturer located in Finland. Approximately 400 people are employed in Finland; the company also operates in Estonia, Latvia, Lithuania, Poland, Sweden, and Iceland. Future opportunities lie in digitalization, enhancing efficiency, competitiveness, and environmental sustainability. Meeting global economic sustainability challenges and the goal of being net-zero by 2040 demands the rapid introduction of new activities and tools in industrial applications. Extensive data sources exist in the manufacturing process, but harnessing data sources for productivity improvement is extremely difficult. Edge AI algorithms have potential advantages for manufacturing processes regarding better prognostics of process quality in real-time to improve productivity.

6. Implementation of Edge AI Solutions

To showcase the integration of Edge AI in smart factories, we present a case study from the paint manufacturing industry. For this purpose, an important challenge was identified, which includes developing computer vision-based AI solutions with an edge computing architecture to address the operational needs of the factory. Edge AI itself is a key innovation, as the computing model allows for faster predictions and decisions on the manufacturing line. Nevertheless, the greatest value will be achieved by extending this architecture to provide insights and predictive analytics. Transitioning from traditional computer vision-based inspection systems to an AI-based architecture takes time and careful consideration of many intricacies. Therefore, the Edge AI solution is presented first, showing how AI models can be adopted for quality inspection effective deployments in smart factories, while paving the way for extended functionalities where greater value is realized.

To this end, a paint manufacturing factory was chosen, specifically for the automatic inspection of painted defects on automotive engine heads. These components are manufactured in a die-casting process, which has very stringent requirements related to dimensions, weight, structure, and properties. To meet these stringent requirements, all the inspected components are painted thermally after manufacturing and before sending them on for machining. These components are then inspected for any painted defects that may affect the functionality of the part. For this purpose, an automatic inspection system enabling faster inspection cycles is required. An in-house solution is implemented. The solution is capable of inspecting the paint quality in terms of detecting and classifying defects based on differences in surface texture in a continuous manner.

As part of this implementation, an Edge AI architecture is deployed that uses an edge device to run the object detection pipelines, which consumes the camera frames, classifies them, and returns the results. The proposed architecture is a critical building block on the path to successfully integrating Edge AI in Smart Factories. Edge AI is an effective solution in the intersection of AI, Edge Computing, and Cyber-Physical Systems in the IoT domain and can be generalizable to many application domains, given their growing relevance in manufacturing and other industries.

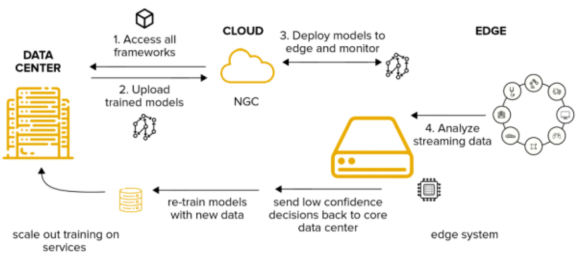

Figure 5: Implementation of Edge AI Solutions

6.1 Technology Stack Overview

To accelerate the path toward smart factories and Industry 4.0, institutional and company-level challenges still need to be resolved. Key among these are a deficiency of industrial standards, a shortage of specialized talent, and a high technology maturity curve. The goal of this study was to create a comprehensive analysis of the practical integration of cutting-edge Edge AI technology in a smart factory context. Factors considered include industry specifications on raw material production and batch processing. A current process flow was analyzed in detail for a paint manufacturer producing materials for ultra-types of consumption and automotive industry sectors. A potential Edge AI technology stack pipeline tailored for this use case was proposed and justified. Specific Edge AI applications were designed and presented for ongoing forecast maintenance and real-time quality control of raw materials based on spectroscopic imagery. Implementation steps were discussed for the design and tuning of the Edge AI models considered. Further experimentation procedures on Edge hardware configurations were also proposed.

Digitalization has triggered a new industrial revolution in which factories are transformed into ecosystems consisting of cyber-physical systems (CPSs) and various intelligent agents. The factories are expected to be smart, providing autonomy for production systems that can coordinate across the organization's boundaries. The concept of a smart factory is the core of this transformation. Driven by the Industrial Internet of Things (IIoT)–there has been a tremendous increase in the scale, diversity, and complexity of production systems and operational data. In addition, the rapid progress of artificial intelligence (AI) technologies, especially Big Data analytics, has significantly enriched the evolving landscape of factory operations.

6.2 Integration Process

Smart factories necessitate the cooperation of information technology (IT) and operational technology (OT) systems to actualize intelligent manufacturing. Nonetheless, current production lines use legacy field devices that do not support new technologies, including Industrial Internet of Things (IIoT). There is an urgent desire to integrate edge intelligence, which can analyze streaming data at the edge, classify products, and detect potential product quality issues. A blue-sky thinking approach is proposed to depict the process of conversion from a conventional painting production line to a smart factory using an aqueous paint type as an example. The conversion path and adjusted payback period are investigated and calculated. The results have implications for other industries in this regard.

The manufacturing industry is increasingly taking advantage of IT technologies to attain the integration of IT and OT systems. On the one hand, by creating real-time connection and understanding between production and enterprise levels, the IT systems intelligently schedule production and optimize resource allocations, which enables advanced decisions making. On the other hand, data digitization and contextualization at the OT level make significant information available for the IT system. However, most enterprises, especially small and medium-sized ones, still face challenges to access data produced by the OT systems and to link them with the corresponding enterprise information. A middleware and two supporting frameworks for affordable manufacturing big data acquisition are proposed. A case study of a billing-based big data acquisition between IT and OT

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levels is conducted for the glass batch production industry. Feasibility analysis proved the workability of the proposed middleware.

In what follows, the challenges of integrating new technology into existing production lines are elaborated on first. Then, as an example, a case study on integrating edge AI into a paint production line is presented to depict the integration process in detail.

6.3 Collaboration with Technology Partners

The introduction of various technologies and the support of various partners in smart factories represent a considerable investment. For production plants, the question is whether this stability will be permanent, as suppliers of frameworks as well as the underlying technologies may not survive. Certain types of applications could integrate with different frameworks or infrastructures, but if these premises are life-critical, there may be a tendency to tightly integrate applications and frameworks into vertical solutions. Interoperability is therefore a key requirement—allowing wider access to AI technologies—but wild integration can lead to system instabilities.

The case reviewed shows how a joint application was successfully developed at the edge and how it worked in a wider context. The biggest risk factors and key success factors are presented, also in relation to the technologies currently being developed. Different businesses and tech partner types have been identified. The actors, their wider roles, and positions in value and technology chains are important to understanding where to direct efforts in moving forward. Certain technologies, especially AI and other predictive analytics, require early sub-optimized development to gain experience with the technology. Other technologies require more cooperation and a common set of needs. Short-term successes may loosen the tight coupling of each application because a systemic instability may cause a large rippling effect. Therefore, strengths or positive experience with a single actor may warrant forming new partnerships, but care should be taken to develop and anticipate wider systemic changes. Else, the current good performance of AI-based applications in production plants may be short-lived, and the initial investments sunk. Well-designed new partnerships or coalitions could bring new successes for manufacturing industries widely in the 2020s.

7. Recommendations

Smart manufacturing systems increasingly rely on highly automated and intelligent equipment, big data, artificial intelligence, and cloud computing. Smart manufacturing realizes integrated and automated on-off, continuous, and intermittent processing throughout the entire process from data collection to analysis of the production line. Analysis generated actionable information throughout the design, manufacturing operation, and maintenance processes. It is characterized by seamless connectivity, comprehensive perceptibility, intelligent control, flexible adaptability, and proactive customization. Today, AI is widely integrated into manufacturing systems with varying degrees of maturity.

Smart factories are needed as a new generation of manufacturing systems. With digital twins, local workshops or manufacturing cyberspace, real-time perception of the physical world, and intelligent anti-operating autonomous and collaborative decision-making are possible via cloud computing. The local IoT perceptual devices, edge servers, mobile edge computing, and AI-assisted methodologies constitute the architecture of new smart factories with a multi-tier distributed architecture. The applications of smart factories cover a diverse range of domains, including a drag-and-drop interface for setting rules in compliance monitoring, minimal supervision on the training data pipelines, and real-time architecture monitoring for rapid and robust deployment of industrial tasks.

The applications of smart factories in factories rely on the design, deployment, and selection of appropriate technologies for customized applications/users' demands. Current studies mainly focus on smart factories in a specific domain, and analysis procedures usually transform the methods to engineering visual mathematical form. The resulting mathematically visual mated formula-based data-driven methods, game-theory-based heuristics or co-evolutions in composite categories, and chemical processing application adjacent rules learning strategy food safety forecasting with outside monitoring, logging, and prompt maintenance modules are still limited to the expertise/profession-oriented designer's ability and knowledge of chemical processing manufacturing systems. Expert transfer involves the undesired performance loss, expensive implementation cost, and prolonged response time in novel applications.

7.1 Best Practices for Implementation

In recent years, manufacturers have adopted edge artificial-intelligence (AI) technologies that eliminate dependence on cloud services and provide real-time monitoring and control of factories. In this regard, a case study in the paint manufacturing industry was performed, where an intelligent edge-device (IED) was designed and developed for real-time temperature monitoring and control for a paint-mixing machine (PMM). Edge-computing algorithms supporting the IED were designed with big-data and AI technologies.

The circuit board design of the device and the mechanical structure design of the installation are also presented. The IED was installed on the PMM, and a cloud-edge collaborative and smart factory platform was successfully built. Connected to industrial sensors, the IED can perform real-time temperature monitoring and control, perform anomaly detection, analyze the running status, and provide factory management reports. Data and models are sent to the cloud for further analysis. A human-machine interface is developed for the interaction between the user and the system. Based on the cloud-edge collaborative platform, the methodology and technology of transforming the traditional factory into a smart factory are studied from the perspective of an integrator or a factory manager.

At the component level, an IED with big-data and AI technologies designed for practical applications is presented. Many works focused on integrated intelligent edge devices based on image processing. However, this device reports running conditions through analytic calculations. Techniques in sensory equipment and circuits usually could be extendable. Thus, a general-purpose low-cost IED that not only provides the designed solution but also a fine foundation for extending other models is suggested. As a design case, the cloud-edge collaborative smart factory platform developed based on the IED will be introduced. The proposed methodology is demonstrated in a paint manufacturing industry.

Such a methodology and model can be replicated in similar scenarios. Aiming at implementing the AI-based techniques, a training platform that could be used to educate engineers is developed. It allows learning from basic knowledge up to edge AI techniques. The knowledge and techniques learned from this work could be extended to other research areas.

Equ 3: Real-Time Viscosity Prediction at Edge

$$\hat{V}_t = f_{\text{Edge}}(T_t, C_t, S_t, pH_t)$$

- $\hat{V}_t$: Predicted viscosity
- T_t: Temperature
- C_t: Colorant concentration
- S_t: Solvent ratio
- pH_t: Acidity

7.2. Strategic Planning for Adoption

An intelligent architecture (IA) platform supporting the edge AI in smart factories has been conceptualized. It contains an advanced technological infrastructure handling distributed and heterogeneous manufacturing equipment that needs the integration of legacy systems. To address the challenge of the quick development of AI algorithms, an edge AI environment with easily accessible AI services has been developed. The platform is realized through a business architecture describing a concrete use case and an industry-friendly integrated architecture detailing the new platform architecture. As a result, the platform ensures the interoperability of legacy systems, provides edge automation and orchestration APIs to application developers, enables easy-to-use integration and ecosystem events for business partners, and adopts standardized ways to create applications. The system is validated in a paint manufacturing context, and the performance of edge ML models is evaluated against cloud ML models using a case study of color prediction.

AI is taking a new focal point within companies, especially since the digitization initiatives driven by Industry 4.0 are focusing on how to automate production processes through the use of advanced technologies like IoT, 5G, Edge Computing, Cloud Computing, etc. Examination of the current state-of-the-art architecture supporting the Edge AI in Smart Factories. Comparison with existing industrial solutions. Identification of industrial gaps and specification of architectural requirements based on the identified gaps on the Edge AI in Smart Factory. Business and integrated architecture of a novel intelligent architecture supporting the Edge AI in Smart Factories.

As the current state-of-the-art architecture, the AIMAPifact platform takes a newly compounded approach to AI by providing an advanced technological infrastructure, an edge AI environment, and an integrated architecture. Process automation, especially in manufacturing industries, usually requires the integration of diverse legacy systems. Although the solution vendors provide various technologies to facilitate a new system to monitor and control the old devices, designing a unified architecture supporting the open compatibility and intercommunication with heterogeneous manufacturing equipment is still a challenge. The current architecture focuses on preparing the data source only, but existing industrial solutions generally need to pay attention to sensors monitoring the equipment and the database, rather than controlling the actuator of manufacturing equipment.

8. Limitations of the Study

This paper takes a long-term perspective towards developing a gradual deployment process of integrated Edge AI in smart factories and delivers an industrial case study from a paint manufacturing company. This case study demonstrates how Edge AI is used to identify and prevent an important defect: the stains of tinters. It also describes the gradual implementation process and facilitates engagement with other companies considering acceptance of Edge AI. The research starts from the perspectives of "what if" and "why so" and iterates back and forth towards understanding essential issues from non-technical layers. The novelty of the Edge AI in the case study lies in preemptively identifying defects instead of post-hoc corrections and the transferred graspability of thermal vision data by machine learning techniques.

Although the gradual deployment procedure in this research could facilitate potential users to construct feasible methods in implementing Edge AI, some more technical discussions should be disclosed to make it more value-added. For instance, edge servers could be further explored—especially how to deal with hardware obsolescence in existing systems that were not particularly built with Edge AI use cases. This research has not addressed the relatively adverse effects of introducing Edge AI, which should also be recognized—for instance, the implications of workers and their authority.

The paper contributes to the academic community by enriching knowledge on essential considerations across technology acceptance processes and engaging in traditional manufacturing industries' expertise in transforming factories to holistic production systems. Moreover, the gradual deployment of Edge AI fills the void between academia and industry on implementation methodology and overcomes the challenges of traditional maturity models by offering a more user-centered view. By documenting a case study, the research presents a feasible approach to gaining a foothold in the Edge AI value chain, as most companies in traditional industries lack the expertise to kick off such solutions.

8.1. Scope of Research

With the advancement of automation equipment and artificial intelligence (AI) technologies, factories are becoming increasingly automated. However, the communication network is limited or non-existent in a few instances. Such factories are known as “dark factories,” a term enjoying widespread popularity among researchers and practitioners in manufacturing automation. Information and data collection, transmission, and processing rely on the intelligent edge of devices in these factories. Edge AI holds the potential to integrate human knowledge (via data-driven models) and machine knowledge (via AI algorithms) at the intelligent edge to fully realize intelligent manufacturing. However, dark factories are diversity driven, and traditional machine learning-based approaches fail to accommodate production diversity. Knowledge-driven AI methods have gained acclaim in dark factories, but they are underexplored in practice with industrial machine tools, especially in terms of integrating multiple human domain knowledge sources across various use cases. The research aims to present a new knowledge-based AI framework and methodology—knowledge-driven edge AI—to depict the full spectrum of AI functions in dark factories. The power of the proposed knowledge-driven edge AI in dark factories is illustrated and validated with collaborative case studies from discrete manufacturing domains. This research strives to provide academic and practical contributions for advancing state-of-the-art knowledge-driven approach to disaster-aided intelligent manufacturing in enabling edge AI research in dark factories.

AI plays a key enabling role in realizing smart manufacturing. Especially with the rapid emergence of low-cost edge devices and affordable and sufficient cloud resources, applying AI techniques close to where data is generated (at the edge of the network) has gained popularity among both researchers and practitioners, leading to an increasing number of edge AI studies and applications in various domains [2]. Factory operation and management, which include multi-tier monitoring, fast-responding fault diagnosis, etc., has become new hot topics in edge AI research and applications in smart factories. However, edge devices in smart factories often suffer from diverse operating conditions and systems. Traditional machine learning (ML)-based edge models require a huge amount of labeled data and processing resources for the retraining and remediation of new operational conditions, rendering them ineffective for addressing the fast-iterating and difficult-to-label demands of smart factory environment diversity.

8.2 Potential Biases

The introduction of an AI-based quality control system in the paint manufacturing industry opened the door to new possibilities for industrial solutions, while allowing companies to shift towards more automated and data-driven operations. However, the data collection and subsequent AI model training process led to multiple challenges, including the impending bias of the models, the dataset size and characteristics, and edge AI model deployment mitigating dataset and model biases in the analyzed application were studied. Three main types of biases were identified and mitigated: bias caused by the input label-quality, bias resulting from having limited and unbalanced dataset samples, and bias thawed by the model deployment in an edge AI environment, with two corresponding solutions proposed. The potential risks for the canvass and exploration of wider solutions after the first deployment were also discussed. Biases can occur in many stages of a data-driven model implementation, and industry focus is currently on data collection and model training. Nevertheless, systematic inspection of bias in multiple stages and comprehensive case studies have not been sufficiently covered in the reviewed literature so far, which limits the possibility to fully optimize edge AI solutions for critical applications with increasing privacy, bandwidth, and energy constraints. Furthermore, while the industrial applications illustrated the evolving nature of AI system biases, model degradation understanding and a wider range of case studies about how to inspect biases in edge AI applications across different industries were still needed.

In addition to gathering datasets that are scalable enough to avoid unwanted model functions, accurate and coherent data labelling is also crucial for the reliability of a wide range of AI-based applications. As skewed distribution is a widespread problem, especially in industry datasets, pre-data processing methods could be introduced in future research as they have shown promising results in database and sampling issues, particularly in spotting infrequent samples. Bias from the input sensor or edge AI environment should also be assessed and ensure robustness coverage of edge environments by simulating multiple cases in testing. Following that, capturing evolving features of the input data and further rebuilding a subset of tested-based models could be part of future study.

9. Future Research Directions

Artificial Intelligence (AI) has been widely adopted in various applications, with a focus on making factories smarter, increasing production efficiency, and improving product quality. To achieve these goals, AI has been integrated with cloud computing for the establishment of cloud-based factory computing and cognitive systems. However, the heavy reliance on the cloud may overlook the advantages of Edge AI, as devices can perform AI actions without the need for transferring large volumes of data to the cloud for processing. This paper elaborates on a novel Edge AI scheme to facilitate intelligent painting defect detection. The proposed scheme is implemented and evaluated in offline and online modes at a real-world paint manufacturing site. The offline option allows engineers in production and quality control to validate the usefulness of AI without requiring modification of existing infrastructure, while the online option can help proactively detect defects in the painting process. Experimental results show that both options can provide satisfactory results for defect detection while supporting the challenge of excessive false positives by conventional persistent-line tracking data processing.

AI has been integrated with various systems to improve production efficiency and product quality in smart factories. Considering extensive data acquired for management decisions in persistent-line painting, RNN has been leveraged to model the production process for flaship anomaly detection. To cope with the information gap between multiple hierarchically distributed databases, AI has been integrated with a service mesh for on-demand resource provisioning and filtering across service instances in distinct clusters. The integration facilitates interoperable service tracing for automatic root cause reasoning through Deep Reinforcement Learning but requires feeding all data to the cloud due to the need for global information.

Despite having Jupyter Notebook integrated with the enterprise resource planning system, an automated huge data processing system for machine learning is absent. This resulted in protracted preprocessing time to convert the data before feeding it to the cloud inference server. Lately, AI has been deployed at the Edge to support immediate detection, and the prerequisite is to determine the features of interest and, subsequently, that the Edge device comes equipped with sufficient computing performance to execute as per design.

9.1 Emerging Technologies

The modern industrial revolution is characterised as Industry 4.0, with emphasis on local manufacturing, customisation and mass personalisation, product and manufacturing system integration, information transparency, and high-performance manufacturing. Attention is being drawn toward the future smart factories of the post-I4.0 generation, addressing the emerging technologies and requirements to integrate additional intelligence into the factories to allow higher value-added manufacturing and enhanced engineering agility. Therefore, the future generation of smart factories is expected to be more affordable, scalable, accessible, and portable (ASAP) to allow effective integration of advanced manufacturing systems by addressing major barriers. Various dimensions of intelligent manufacturing systems are analysed, such as integration of Cloud/edge-based, big data, Artificial Intelligence (AI), and machine learning (ML) technologies to offer unbroken connectivity and swift accessibility to a larger amount of data in hybrid architectures of factories. AI technologies are enablers to higher-value manufacturing in this manufacturing revolution era, allowing advanced engineering functionalities in data-driven scenarios.

To design the intelligent smart factories, AI systems implementing the AI workflows such as production prediction, real-time process optimisation, anomaly detection, quality prediction, and energy performance in production planning scheduling are emphasised. The popular AI technologies for the design of smart factories are examined, such as deep learning, machine learning, evolutionary algorithms, and fuzzy logic systems. Based on these advancements, a fictitious flexible smart factory illustrating the flexible batch mode of operations of intelligent systems deployed for manufacturing industrial components and assembly approaches with two demonstrators is described, then the use cases are illustrated and vision/assessments are provided. Advanced technologies are emphasised to enhance the manufacturing processes of the 21st century, as well as achieving new functional capabilities such as miniaturisation, additive layer processes, bio/process engineering, nanostructure, high tenacity with low weight materials, flexibility, modulability, overcoming human limitations, and improving working conditions.

9.2 Longitudinal Studies

Longitudinal studies are widely used in many academic disciplines, incorporating qualitative or quantitative data along a time dimension. Such studies are particularly popular in fields that study phenomena that evolve over decades, such as education, social science, epidemiology, and clinical research. The study is usually interested in relation to time: how a given variable changes; examining trends; if observed changes can be interpreted as systematic changes, etc. Various statistical methods are used in the analysis of longitudinal data, including discrete methods, time series methods, and continuous methods.

Most of the longitudinal studies have been conducted in statistics and epidemic studies. The literature for longitudinal studies in engineering is rare but growing. Long-term mechanical testing is often required to provide empirical data for life and durability predictions of materials, components, or systems. Methods employed in longitudinal studies to analyze material fatigue durability data include, but are not limited to, data declustering, multivariate regression, maximum likelihood methods, and Bayesian approaches. There are some evolutionary degeneration study methods investigating building or civil engineering infrastructures.

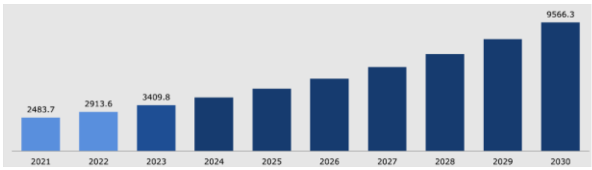

Figure 6: Integrating Edge AI in Smart Factories

It is worth noting that there is engineering interest in longitudinal studies, but there is no systematic compilation of modern longitudinal study methods of any significance across engineering disciplines. The goal of this task is to provide a systematic yet concise summary of longitudinal study methods for an engineering audience. Important contributions from other disciplines will be considered, and all methods will be in the language of engineering and application-oriented. Longitudinal studies of all time scales will also be considered.

10. Conclusion

A new production paradigm is urgently needed to innovate enterprise manufacturing by adopting a digital transformation. It is especially crucial to uniformly combine the elements of Industry 4.0 such as production monitoring, data integration, and schedule optimization, improving the dynamic adaptability of industrial manufacturers to external disturbances and demands and enriching service diversity. This research develops a framework that integrates Edge AI to guarantee production capacity with efficiency vis-a-vis the existing Paint Shop 2 at JPT. The implementation of AI algorithms in the MES-LNL system is also described. With respect to existing Edge AI technologies to resolve process detection categories, it is feasible to further segregate the MI anticipated from the claims made toward each category and quantitatively assess the value of intelligence. A standardization of factory structure that divides monolithic factories into smaller interconnected Edge Farms has been proposed for overseas and significantly large factories.

Aside from content gaps such as equipment health detection and manual intervention disturbance processing ability, gaps exist with regard to implementing the use of actual Edge AI. With regard to AI performance gaps with respect to RT852, the tuned MRF model without post-processing utilized was not robust against no/edge defects and defects larger than the training data. Performance with regard to the inference environment will be affected considering the integration of an actual mobile edge device.

In order to expand the use cases hints toward insensible nuisance detection, Edge AI deployment, and trimming of low-intelligence production, the aforementioned performance degradation and content gaps must be dealt with. A frame provision is proposed to guide the next stage of the preliminary development system toward robust and production-ready AI. Future work includes stepwise implementation roadmapping and optimization of the site plant-wide monitoring system level 1 unification.

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