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A Method-centric Survey of Artificial Intelligence Techniques in Industrial Environment’s

[1, 2, *] Ietezaz ul HASSAN, [1, 2] Krishna PANDURU, [1, 2] Daniel RIORDAN and [1, 2] Prof. Joseph WALSH

[1] IMaR Research Centre, Munster Technological University, V92 HD4V, Tralee, Ireland
[2] School of Science, Technology, Engineering, and Mathematics,
Munster Technological University, V92 HD4V, Tralee, Ireland
[*] E-mail: Ietezaz.Ul.Hassan@mymtu.ie

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Abstract: Artificial Intelligence (AI) is revolutionizing modern production through the adoption of data-driven decision-making, predictive maintenance, autonomous systems, and high-precision quality control. This work presents an enhanced and method-centric analysis that restructures the landscape of AI in industrial settings through a new conceptual taxonomy, a systematic review based on learning paradigms, and a cross-mapping of AI approaches with industrial settings. The study includes real industry case studies to demonstrate how AI is implemented in reality. The study analyses key challenges such as data imbalance, interoperability gaps, explainability, real-time limits, and workforce skill limitations. Overall, this review presents a comprehensive and up-to-date perspective that improves knowledge of how AI methods progress manufacturing while highlighting the technical and operational constraints that must be addressed in order to develop reliable, scalable, and autonomous industrial systems.

Keywords: Artificial intelligence, Advanced manufacturing, Technological advancement.

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1. Introduction

Manufacturing is the process of transforming raw materials into finished products using labour, equipment, machinery, or technology [1]. Whereas, advanced manufacturing refers to the ongoing evolution of manufacturing methods, expertise, and techniques to meet the societal requirements driven by demand and economic expansion. The national initiatives of the United States, Japan, Europe, and other countries worldwide have highlighted the importance of robust, healthy advanced manufacturing industries [2]. Industrial production and consumer products profit greatly from state-of-the-art advancements in manufacturing techniques and systems.

AI is revolutionizing industries by allowing complex system design, production, monitoring, and maintenance. Recent manufacturing facilities incorporate sensors, robotics, digital twins, automation platforms, and large-scale data pipelines, providing intelligent decision-making and autonomous operations [3]. Despite significant advancements, the application of AI in manufacturing remains distributed and constantly evolving [4]. Machine learning, deep learning, generative models, and reinforcement learning technologies are used for predictive maintenance, quality inspection, process optimisation, and autonomous manufacturing [5]. A prior version of this study presented a comprehensive overview of AI applications in Computer Numerical Control (CNC) machining, robotics, and additive manufacturing [1]. This updated journal version presents a methodological survey to better understand how various AI paradigms contribute to manufacturing in industrial environments.

1.1. Contributions

This journal version includes several new contributions not present in the conference paper. Initially, a conceptual review of AI methodologies, including learning-based AI, physics-informed models, edge and cloud AI, knowledge-based systems, ensemble AI, and autonomous decision-making systems, is presented. This entire survey is organised around AI methods rather than manufacturing applications, resulting in a clearer and more comprehensive comparison. This survey also includes a mapping of AI approaches to real-world industrial use cases and highlights the implementation methods and applications.

The remaining sections of the article are organised as follows: Section 2 presents the taxonomy of AI in industrial settings, and Section 3 presents a systematic review of AI techniques. Section 4 maps AI techniques in industrial environments, while Section 5 includes case studies of AI applications in different fields. Finally, in Section 6, the challenges related to integrating AI in an industrial setting are reviewed, and the analysis is concluded in Section 7.

2. Taxonomy of AI in Advanced Manufacturing

This section introduces a conceptual hierarchy of AI methods and deployment modalities in industrial environments. AI methods employed in industrial settings can be defined as learning-based AI, physics-informed models, edge AI & cloud AI, knowledge-based systems, real-time & offline AI, ensemble AI, and autonomous decision-making systems. These methods, their types, manufacturing applications, and their pros and cons are discussed in the subsections below.

2.1. Learning-based AI

Learning-based AI is a type of AI that learns patterns, trends, and features from labelled or unlabelled datasets [6]. Learning in learning-based AI can be characterised as supervised, unsupervised, or semi-supervised based on the type of data available. Supervised learning is a form of learning in which an algorithm learns from labelled data. It can be used to tackle regression or classification problems and includes models like linear models, random forests, decision trees, XGBoost, Convolutional Neural Networks (CNNs), Transformers, and so on [7]. Whereas unsupervised learning is a type of learning in which an algorithm learns from unlabelled data in order to discover hidden patterns. It includes methods such as DBSCAN, K-means, isolation forests, autoencoders, and others that can be used to solve clustering, density estimation, and anomaly detection problems [8]. Self-supervised and semi-supervised learning, on the other hand, are types of learning that minimise the requirements for large, human-labelled datasets by establishing their own labels or using a combination of labelled and unlabelled data [9]. It could be employed in a number of applications, such as anomaly detection. Similarly, reinforcement learning is a type of learning in which an agent learns to make a series of decisions by trial and error in order to achieve a goal, and it could be used for both model-free and model-based reinforcement learning for scheduling and control [10].

Learning-based AI has applications in predictive maintenance, process optimisation, quality inspection, defect detection, anomaly detection, and scheduling [11]. It is employed in a full pipeline, that includes data collection pipelines, a feature engineering process, and end-to-end sensor to output models. Learning-based AI algorithms are useful for extracting patterns from large datasets, as they are flexible and perform well on perception (prediction) tasks [12]. However, the associated challenge with learning-based AI systems is that they require huge amounts of data, have limited interpretability, and face challenges, especially if there is a change in domain.

2.2. Physics-informed Models

Physics-informed models are AI models that use known physics, such as material models, conservation laws, and mechanistic process equations as part of the learning pipeline. Physics-informed models include grey-box models and physics-informed neural networks [13]. Physics-informed neural networks are neural network that incorporates physical rules, such as differential equations, into the learning process. A grey box model is a modelling method that combines prior knowledge and data, combining the physics-based components of a white box model using AI [14].

These models are quite useful, especially if physics models exist but are incomplete or costly. In general, it is used to pre-train models. In an industrial setting, it is used for process simulation, defect generation modelling, closed-loop process control with physical assurances, and material behaviour prediction [15]. These models are well-known for generalising from limited data, generating physically consistent outputs, and extrapolating within defined ranges. However, the associated challenge with these models is that they are computationally expensive and require precise underlying physics and approximations.

2.3. Edge & Cloud AI

Edge AI refers to the training or testing of AI models on a local device, such as a mobile phone or a computer. Because it is closer to the sensors or actuators, it can make decisions in real-time and with lower latency [16]. It has constraints which include limited compute power, energy, memory limits, and real-time requirements [17]. It has a wide range of applications, including anomaly detection for overall equipment effectiveness, sensor fusion for robots, safety interlocks, and many more.

Cloud AI, on the other hand, refers to the integration of AI with cloud computing, that allows users to access and use AI tools and services via the internet without the need for an on-premises infrastructure [18]. Its features include large-scale training power, global optimisation across several machines or sites, and historical analytics. It can be used for production planning, large-batch retraining, fleet-level predictive maintenance, and a number of other purposes [19]. However, it is limited by communication latency and privacy concerns when transmitting raw sensor data from a local device to a cloud platform or accessing data from the cloud platform.

The most effective strategy to balance the challenges of edge and cloud is to use the edge for the majority of inference and the cloud for periodic model updates [20].

2.4. Knowledge-based Systems

A knowledge-based system is a computer software that solves problems, makes decisions, and operates similarly to a human expert [21]. It can encode domain knowledge in the form of rules, logic programmes, symbolic models, and ontologies. In addition, semantic models and ontologies could be used to represent a process. Similarly, symbolic planners and constraint solvers could be used to generate design rules and sequence processes.

It can be used in manufacturing to design processes, encode safety limits, perform quality compliance checks, and support decision guidance [22]. When machine learning confidence is low, a knowledge-based system can be combined with a learning system to ensure that constraints are satisfied [23].

Knowledge-based systems are often useful, especially because they are simple to set with strict constraints, trace decisions to rules, and are interpretable. However, it can't be done to generalise from data or when rules are insufficient.

2.5. Real-time and Offline AI

In real-time AI, decisions are made within a certain time frame and are commonly used in control loops. It has applications such as immediate quality correction, closed-loop control, and safety monitoring. Offline AI, on the other hand, performs computations offline and is commonly used for design, scheduling, and model retraining. Offline AI applications could include digital twins, simulation, long-horizon scheduling, and/or process optimisations.

Offline systems have a higher computing cost and can use more complicated models, but real-time systems require predictable latency and are limited by computations.

2.6. Ensemble AI

Ensemble AI refers to architectures that intentionally combine two or more paradigms to address the shortcomings of a single AI approach [24]. It can make use of a number of patterns, including parallel ensembles, neural symbolic systems, or model-checked machine learning [25]. In parallel ensembles, the outputs of multiple models are combined using meta learning, weighted averaging, or voting [26]. On the other hand, neuro symbolic systems combine symbolic reasoning with neural sensing to make high-level decisions [27]. While model checked machine learning requires a formal verification process before machine learning can be applied.

In industrial settings, it could be used to create mission-critical controllers, digital twins that combine simulators plus learnt corrections, high-reliability inspection pipelines, and so on [28]. It provides advantages, including interpretability and reliability, that can improve both safety and performance. However, it is also limited by the method's complexity, which can be difficult to comprehend and could require costly infrastructure.

2.7. Autonomous Decision-making System

Autonomous decision-making systems are those that can change an environment or process with very little human intervention, combining perception, planning, and control [29]. Autonomous robotic agents and self-scheduling and dispatching are well-known subtypes of autonomous decision-making systems [30]. Autonomous robotic agents use sensing, planning, and motion control, whereas autonomous scheduling and dispatching use dynamic job shop scheduling via reinforcement learning or optimisation.

Autonomous decision-making systems require a high level of safety, runtime verification, human intervention, explainability [31], and regulatory compliance.

3. Systematic Review of AI Techniques

This section presents a systematic review of AI approaches, organised by methodology.

3.1. Supervised Learning

Supervised learning is a type of machine learning in which AI models are trained on labelled datasets in order to predict results. This type of learning is most commonly used in industrial settings. The most often used algorithms in the supervised learning domain are logistic regression, decision trees, support vector machines, gradient boosted trees, random forests, and neural networks for classification and regression. Supervised learning algorithms are used in manufacturing for predictive maintenance [32], quality prediction [33], tool wear estimation [34], and energy consumption prediction [35].

This type of learning is very helpful when labels are provided with the data. The models in this category can be validated using techniques such as holdout, cross-validation, and others. However, getting the labels with the data can be problematic at times, and this causes challenges in this type of learning.

3.2. Unsupervised Learning & Anomaly Detection

Unsupervised learning is a type of learning in which methods or algorithms are used to extract patterns from data without using labelled datasets. Gaussian mixture models, autoencoders, isolation forests, k-means, and other methods are commonly employed in unsupervised learning to perform clustering, anomaly detection, and density estimation. In industrial settings, it can be used to detect machine defects at an early stage [36], outliers in sensor streams [37], processing drift monitoring [38], and rare defect detection.

Unsupervised learning works well with unlabelled data, which is common in industrial settings when detecting unexpected or unusual defects [39]. However, one associated challenge with unsupervised learning is evaluation, which is extremely difficult because no labels are given. It is also extremely sensitive to noise and scaling [40].

Recent breakthroughs in this area for industrial applications include autoencoder based anomaly detection, which has proven to be quite beneficial for detecting faults or abnormalities as anomalies [41]. Hybrid clustering techniques, when combined with thresholding systems, have also proven their importance in enhancing interpretability in industrial settings.

3.3. Deep Learning

Deep learning is a subfield of machine learning that uses multilayer neural networks to automatically learn features from raw data such as images and signals [42]. CNNs, Recurrent Neural Networks (RNNs), Long Short Term Memory (LSTM), Gated Recurrent Unit (GRU), and transformers are the most commonly used deep learning algorithms for fault detection in industrial applications [43]. CNNs are commonly used to analyse images and spectrograms [44], while RNN's, LSTMs, and GRUs are used to process time series data [45]. Deep learning is highly useful in industrial settings for visual inspection [46], failure prediction [47], anomaly detection [48], and so on. It could detect defects, scratches, cracks, or faults using vibration, acoustic signals [49], or other types of signals, which is highly useful in industrial settings.

Deep learning is important because it eliminates the need for feature extraction by automatically learning hidden features and patterns from raw data [50]. However, the challenges with deep learning are that it requires huge amounts of data, a GPU for training, and have limited interpretability [51].

3.4. Reinforcement Learning

Reinforcement learning is a type of AI learning in which an agent learns actions through trial and error as it interacts with the environment. Some well-known reinforcement learning algorithms include the Deep Q-Network (DQN) [52], Double DQN (DDQN) [53], Proximal Policy Optimisation (PPO) [54], and many others. The DQN uses a neural network to learn Q values (which correspond to state-action values). The DQN performs well in discrete action areas and stabilises training using an experience replay and a target network. The DDQN, on the other hand, improves the DQN by lowering Q-value over-estimation by separating action selection and action evaluation, as well as being more stable and accurate. On the other hand, the PPO is a policy gradient approach that avoids huge policy updates by using a clipped objective. It is even more stable and commonly used in robotics and control applications [55].

Reinforcement learning can be used in industrial settings such as robotic path optimisation [56], dynamic scheduling in job shop environments [57], real-time process control [58], and energy optimisation in industrial systems. Reinforcement learning has the advantage of being able to adapt to dynamic contexts and learn complex control strategies that go beyond rule-based logic [59]. The associated challenge with reinforcement learning is that exploration can be hazardous in real machines [60]. Another challenge is that simulation or digital twins are required for training and verification.

Recent advances in reinforcement learning have drawn attention while ensuring the safety of reinforcement learning algorithms. The application of digital twins for training reinforcement learning agents prior to deployment has also grown as well [61].

3.5. Natural Language Processing (NLP)

NLP allows the analysis, interpretation, summarisation, and search of textual data by machines, computers, or software systems [62]. Transformer-based models such as BERT, GPT-based models [63], document categorisation, named entity identification, summarisation, and information extraction are among the methods that NLP could use [62]. In an industrial setting, NLP could be used to automatically extract insights from maintenance logs, parse safety documents and machine manuals, generate reports, and use text-based queries to improve operator support systems

It provides advantages because it can handle unstructured data and is useful for expert system augmentation and knowledge management. The associated challenge in NLP is that technical jargon and abbreviations could compromise the accuracy [64]. It also requires domain-specific fine-tuning.

3.6. Generative AI

Generative Adversarial Networks (GANs), Variational Auto-Encoders (VAE's), diffusion models, and Large Language Models (LLM) based design optimisers are examples of well-known generative AI models [65]. In an industrial setting, generative AI could be used to generate CAD models automatically [66], optimise process parameters, create material microstructures [67], and generate's defects at the image or signal levels for deep learning model training [68].

It reduces design time, generates synthetic data for model training, and could allow the exploration of huge design areas, all of which could be very helpful [69]. However, it may be limited due to reliability and physical feasibility constraints. It also requires precise boundaries and regularisation, which presents a challenge [70]. Physics-informed generative models are becoming increasingly popular in manufacturing design generation [71]. Similarly, the synthetic datasets provide an opportunity for improving accuracy in low-data inspection tasks.

4. Mapping AI Methods in Industrial Context

This section provides a mapping of AI approaches to industrial domains. This structure demonstrates how a certain AI method operates in an industrial environment.

4.1. Supervised Learning Methods in Industrial Settings

Supervised learning AI approaches such as Support Vector Machine (SVM), random forest, Artificial Neural Network (ANN), naive Bayes, decision tree, and others could be applied in industrial settings such as in additive manufacturing, assembly lines, and CNC machining. In additive manufacturing, supervised learning approaches can be used to classify defects from signals and images, thus allowing condition monitoring-based maintenance [72]. In CNC machining, supervised AI algorithms could be employed to estimate surface quality or predict tool wear [73]. These methods have the capability to provide high accuracy and be more interpreted, but they require a labelled dataset, which is difficult to obtain in industrial scenarios. Similarly, these approaches have limited generalisation capability. In additive manufacturing, supervised AI algorithms could be used to detect defects from both signals and images [74]. Although it provides fast training and is ideal for inspection, but getting accurate labels (ground truth) from input values is quite challenging. In assembly lines, it could be used for quality control and visual inspection [46], since it allows reliable real-time detection, but it is still vulnerable to lighting and variations. The Table 1 below summarises these methods, along with their applications, advantages, and disadvantages.

Table 1. A summary of Supervised learning methods in industrial environments.

Domain	Applications	Advantages	Disadvantages
CNC Machining	Tool wear prediction. Surface quality estimation	High accuracy Interpretable	Labelled data. Limited generalization.
Additive manufacturing	Defect detection from signals and images	Fast training Good inspection capability	Quality labels.
Assembly lines	Quality control. Visual inspection	Reliable Real time detection	Sensitive to variations. Sensitive to lighting.

4.2. Unsupervised/Anomaly Detection Methods

Unsupervised learning methods could be used widely in industrial settings for predictive maintenance, robotics, and anomaly detection [75]. In predictive maintenance, clustering methods such as k-means clustering or DBSCAN algorithms can be used to identify anomalies in sensor data. It is useful because these approaches do not require labels, however the challenge is that they are difficult to tune. On the other hand, autoencoders can be used unsupervised to detect defect patterns in areas such as robotics [41]. The autoencoders are trained on healthy data in order to recreate the original data, but when there is faulty data, they are unable to generate the faulty data, resulting in a high reconstruction error. It is useful because it can identify unknown defects. However, the reconstruction threshold can be hard to determine. Unsupervised AI approaches could be used as well in machines to find outliers in machine data, using statistical anomaly detection methods [76]. These approaches are simple and lightweight, but they may produce a large number of false positives. Table 2 below summarises these methods, along with their applications, advantages, and disadvantages.

Table 2. A summary of Unsupervised learning methods in industrial environments.

Domain	Applications	Advantages	Disadvantages
Predictive maintenance	Sensor based anomaly detection	No need for labels	Hard to tune
Robotics	Defect patterns extraction	Detect unknown defects	Defining reconstruction threshold is a challenge.
Machines	Outlier based fault detection	Simple and lightweight	High false positives

4.3. Deep Learning for Industrial Fault Detection

Deep learning algorithms such as CNN, RNN, LSTM, GRU, and transformers could be used in manufacturing for casting, visual inspection, welding, condition monitoring, and quality inspection [42]. The CNN could be used to detect surface defects in visual inspection, welding, or casting, where it gives high precision while maintaining a robust feature ability [77]. However, one of the challenges that CNN encounters in such an industrial scenario is the requirement for a huge dataset. On the other hand, the RNN and LSTM could be used for condition monitoring, detecting defects from data such as vibration, temperature, and pressure. They are valuable, because they can capture temporal dependencies [45], but they may also result in unstable training. Similarly, transformer architectures could be employed for quality inspection [44], as they allow for high-resolution defect classification. It is important in terms of providing better global context, but the challenge is that it is computationally expensive. The Table 3 below summarises these methods, along with their applications, advantages, and disadvantages.

Table 3. A summary of Deep Learning methods in industrial environments.

Domain	Applications	Advantages	Disadvantages
Visual inspection	Surface defect detection	High precision Robust features	Large datasets
Condition monitoring	Vibration, temperature, pressure based defect detection	Temporal modelling capability	Instable training.
Quality inspection	High resolution defect classification	Good global context.	Computationally expensive

4.4. Reinforcement Learning for Optimization & Control

Reinforcement learning methods such as Q-learning, deep reinforcement learning, and multi-agent reinforcement learning can be applied to robotics and task planning [55], process control, and intelligent factories [56]. In robotics and task planning, it can play a significant role in optimising motions by learning from interactions. But the challenge here is that convergence is slow. In process control, reinforcement learning methods such as deep reinforcement learning can be used for adaptive machining and energy optimisation [59]. It provides optimal continuous control in certain scenarios, but it is extremely difficult to implement in real factories. On the other hand, in smart factories, reinforcement learning can be used for multi-robot coordination, providing advantages such as adaptation to complex tasks. Table 4 below summarises these methods, along with their applications, advantages, and disadvantages.

Table 4. A summary of Reinforcement learning methods in industrial environments

Domain	Applications	Advantages	Disadvantages
Robotics Task planning	Motion optimisation Items picking	Learn from interactions	Slow convergence
Process control	Adaptive machining Energy optimisation	Optimal continuous control	Hard to deploy in real factories.
Smart factories	Multi-robot coordination	Scales to complex tasks.	Stability problems.

4.5. NLP in Manufacturing Documentation & Knowledge Representation

In a manufacturing scenario, NLP could be used for quality documentation, maintenance logs, and compliance documentation. Automated defect report classification could be achieved with NLP algorithms similar to those used for text classification in quality documentation [62]. It is quite useful because it reduces manual efforts, but the drawback is that it requires a limited amount of tagged text. On the other hand, maintenance logs can be generated using LLMs, which can predict appropriate insights, information, and patterns from text. It can handle unstructured data; however, there is a risk of illusions. However, in compliance documentation, sequence tagging can be used to retrieve important details. It is helpful to automate documentation, but it requires domain-specific training [64]. The Table 5 below summarises these methods, along with their applications, advantages, and disadvantages.

4.6. Generative AI for Design & Process Innovation

Generative AI models [65], such as GANs and diffusion models could be used in manufacturing to develop product layouts and for additive manufacturing. The GAN could be used to generate shapes, synthesis defects, and other features that could result in new design possibilities [66]. However, the associated challenge is that it could cause instability while training. Similarly, in additive manufacturing, diffusion models could be used to look into process parameters. It is extremely helpful because it can generate high-quality results, but it also requires a lot of computing power [78]. The Table 6 below summarises these methods, along with their applications, advantages, and disadvantages.

Table 5. A summary of NLP methods in industrial environments.

Domain	Applications	Advantages	Disadvantages
Quality documentation	Automated fault report classification	Reduces manual workload	Limited to labelled text.
Maintenance logs	Predictive insights from text	Handles unstructured data	Risk of illusion.
Compliance documentation	Retrieving critical parameters	Automates documentation.	Domain specific training required.

Table 6. A summary of Generative AI methods in industrial environments.

Domain	Applications	Advantages	Disadvantages
GANs	Product design	Defect synthesis Shape generation	Instable training.
Additive manufactu-ring	Process parameter exploration	High quality generation	High compute demand

5. Industrial Case Studies

This section presents examples of real-world industrial applications of AI approaches.

5.1. Predictive Maintenance

Machines in industrial settings struggle with unexpected breakdowns and downtime. Predictive maintenance on the other hand, is a maintenance technique that uses condition monitoring to find the remaining useful life of an equipment [32]. It includes condition monitoring, machine learning, and anomaly detection models. Predictive maintenance allows early detection of faults, real-time data over factories, and reduces downtime and operational expenses.

5.2. Industrial Equipment Health Monitoring

Continuous monitoring could prevent catastrophic failures of industrial equipment such as turbines, compressors, and so on. It can use supervised AI algorithms, Bayesian reliability estimation approaches, and physics-based models. It can help to accurately predict equipment degradation [76], minimise repairs and failures, and improve asset performance management.

5.3. Autonomous CNC and Robotic Systems

Manual programming in CNC machines and robotic systems is both error-prone and time-consuming [73]. Deep learning-based approaches for visual inspection, as well as reinforcement learning methods for optimising robot motions [56], are especially important because they are neither time-consuming nor error prone. It has various advantages, including increased flexibility in manufacturing lines, improved defect detection using AI models, and the ability to learn optimal movements automatically.

5.4. Autonomous Manufacturing Line

AI can also play an important role in autonomous production lines, such as those used by Tesla to produce large volumes of electric automobiles, which all require precision, speed, and rapid reaction to design changes [79]. Deep learning models are especially helpful in these manufacturing lines for visual inspection, robotic optimisation, and real-time control algorithms. These AI models could provide benefits such as automatic defect correction, fast feedback chains, improved productivity and production performance.

5.5. Connected Factories

AI methods such as anomaly detection models, cloud models, time series forecasting, and Edge AI models could be used for predictive maintenance at the factory level, generating real-time alerts, optimising processes, reducing waste and saving energy [80], which all contributes towards the connected factories.

6. Challenges

The integration of AI into the industrial environment for production has many challenges, which are outlined below.

6.1. Data Imbalance and Data Quality Issues

In the majority of cases, datasets collected in industrial environments are composed of normal rather than faulty samples. This data imbalance could lead to biased models, resulting in poor detection of faults [81]. The noise and missing values in the collected data could even reduce the performance further. Overall, data imbalance and data quality issues could result in reduced generalisation.

6.2. Lack of Interoperability and Standardization

Another challenge in integrating AI in industrial settings is that equipment may be from different suppliers and use incompatible protocols [82]. As a result, integrating AI with PLCs, sensors, or ERP systems is difficult because they do not all share a common data format or uniform API standards. These challenges increase deployment time and implementation costs.

6.3. AI Transparency and Explainability

Another challenge that may occur while implementing AI in an industrial setting is explainability and transparency, because AI models, especially deep learning models, operate as a black box, which prevents operators from simply understanding the underlying decisions [83]. In addition, a lack of explainability might cause trust issues in safety critical activities.

6.4. Real-time Processing Constraints

Control systems, which are time-critical systems, require a model with milliseconds of latency, but complex AI models, especially deep learning models, sometimes have higher latency. In addition, synchronizing several high speed data streams is also challenging, which could limit the generalization of AI models for non-critical tasks [84].

6.5. Skills Gap

The integration of AI in an industrial setting requires that operators be familiar with AI, data engineering, and programming. Whereas the operators lack these skills [85], empowering them with these skills could end up in a substantial training cost for small and medium-sized factories, causing slow adoption and relying heavily on vendors.

7. Conclusions

This article reveals that while AI is currently shaping the future of industrial environments, its full potential has yet to be explored. This survey demonstrates both progress made and gaps that remain by using an updated hierarchy, a method-centric review, cross-domain mapping, and real-world industrial case studies.

AI methods, including traditional machine learning, deep and generative models, are increasingly used in predictive maintenance, quality control, robotics, and autonomous production. However, data limitations, challenges with interoperability, real-time requirements, and workforce availability remain to limit their deployment.

The analysis presented in this survey highlights a clear conclusion: AI will continue to promote industrial innovation, but future success is dependent on building more explainable, dependable, and scalable solutions. Collaboration among researchers, engineers, and industry leaders will be important as the technology grows to allow truly intelligent, safe, and autonomous production environments.

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