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A review of artificial intelligence applications in manufacturing operations

Siby Jose Plathottam | **Arin Rzonca** | **Rishi Lakhnori** | **Chukwunwike O. Iloeje**

Energy Systems and Infrastructure Analysis Division, Argonne National Laboratory, Lemont, Illinois, USA

Correspondence
Siby Jose Plathottam and Chukwunwike O. Iloeje, Energy Systems and Infrastructure Analysis Division, Argonne National Laboratory, Lemont, IL 60439, USA.
Email: splathottam@anl.gov and ciloeje@anl.gov

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Abstract

Artificial intelligence (AI) and machine learning (ML) can improve manufacturing efficiency, productivity, and sustainability. However, using AI in manufacturing also presents several challenges, including issues with data acquisition and management, human resources, infrastructure, as well as security risks, trust, and implementation challenges. For example, getting the data needed to train AI models can be difficult for rare events or costly for large datasets that need labeling. AI models can also pose security risks when integrated into industrial control systems. In addition, some industry players may be hesitant to use AI due to a lack of trust or understanding of how it works. Despite these challenges, AI has the potential to be extremely helpful in manufacturing, particularly in applications such as predictive maintenance, quality assurance, and process optimization. It is important to consider the specific needs and capabilities of each manufacturing scenario when deciding whether and how to use AI in manufacturing. This review identifies current developments, challenges, and future directions in AI/ML relevant to manufacturing, with the goal of improving understanding of AI/ML technologies available for solving manufacturing problems, providing decision-support for prioritizing and selecting appropriate AI/ML technologies, and identifying areas where further research can yield transformational returns for the industry. Early experience suggests that AI/ML can have significant cost and efficiency benefits in manufacturing, especially when combined with the ability to capture enormous amounts of data from manufacturing systems.

KEYWORDS

AI, AI challenges, industry automation, industry operations, machine learning, manufacturing industry

Rishi Lakhnori and Arin Rzonca were Research Intern at Argonne National Laboratory at the time of contribution.

1 | INTRODUCTION

1.1 | Overview

The transformation of artificial intelligence (AI) and machine learning (ML) from computer science theory into real-world technologies is a key enabler of the fourth industrial revolution (Industry 4.0), to the extent that it integrates AI/ML and other emerging technologies to transform industry. Governments and industries worldwide have recognized the strategic implications of AI/ML technologies and launched a host of initiatives seeking to explore and capitalize on this new revolution by incorporating of AI/ML into manufacturing and industrial processes. These initiatives involve bringing AI/ML onto the factory floor[1,2] and integrating information technology advances (e.g., Internet of Things [IoT], big data analytics, edge computing, and cybersecurity) into the existing process automation infrastructure.[3] With such AI/ML solutions, the manufacturing industry can leverage the vast amounts of data created by measurement devices on the factory floor to improve manufacturing efficiency, productivity, and sustainability.[4–7]

Incorporating AI into manufacturing is considered distinct from digitization and integration of information technology. The latter may be seen as a pre-requisite for the former, that is, digitization and information technology provide the infrastructure required to implement AI/ML-based solutions. In the same vein, AI/ML solutions can provide additional value for established digitization and information technologies by extracting new, actionable intelligence from data, such as better process control paradigms or optimized preventive maintenance schedules which leverage large volumes of historical operations and failure mode data, as well as better business insights from data analytics. Early experience in the industry demonstrates the potential of AI/ML to bolster cost, efficiency, and productivity gains for a wide range of applications. These applications include predictive maintenance to improve real-time monitoring of equipment performance to reduce the likelihood of unexpected failures; quality assurance to identify product imperfections and support factory floor error detection; energy forecasting to improve sustainability and manage energy needs; safety and security to mitigate cybersecurity risks and rapidly detect and flag unsafe practices; generative design to drive rapid topology optimization in product design, and experimentation to simulate normal and anomalous behavior without needing to run disruptive tests on the actual manufacturing process.[8]

Incorporating AI into manufacturing processes and facilities faces significant challenges. First, it can be capital-intensive, in terms of the hardware and software infrastructure required to collect and process data. Second, it can be challenging to recruit additional human resources with AI/ML expertise, and train existing personnel for new roles involving AI/ML solutions. Third, interpreting predictive outcomes and deriving and implementing actionable intelligence is nontrivial. Finally, several aspects of AI/ML technology are not fully mature, and there is a non-zero probability that implementation might not yield sufficient return on investment to justify it.[4] Additional challenges include, (a) unintended security risks could arise when AI/ML solutions are introduced into industrial control systems, (b) computationally intensive AI/ML models could increase the energy and environmental footprint of manufacturing facilities, (c) AI/ML techniques have the capability to take on some of the higher level decision making responsibility, and by doing so, fundamentally alter the nature of human-machine interaction in a manufacturing plant. However, there is limited trust in the reliability of AI/ML techniques, lack of interpretability in the outputs from AI/ML models, and behavioral inertia towards the culture change that will be brought about by introducing AI/ML to manufacturing, and (d) the field of AI/ML is constantly evolving, which makes implementation challenging, especially for firms that are not computer science technology-oriented, and without ready access to required ML expertise.[9] However, as research continues to develop, these areas of concern can become minimized through, for example, (i) the use of generative models to supplement sparse datasets, (ii) developing power and memory-efficient computing architectures for IoT devices, (iii) developing appropriate metrics to quantify confidence in decisions made through AI/ML models, and (iv) the growth of a wide variety of automated AI/ML tools provided as "Software as a Service (SaaS)" that save individual companies the need to build their own in-house AI/ML capability.

1.2 | Study approach

Literature review on AI/ML in manufacturing primarily focused on three sources, namely, academic literature, blog posts, and industry reports. In this review, we prioritized academic literature, and used other sources for specific use-case illustrations. The initial survey started with over 200 sources, which we narrowed down to around 100 sources using the following criteria: (a) published within the last 10 years; (b) focuses on AI/ML applied to manufacturing; (c) uses mature AI/ML techniques which have found success in non-manufacturing industry applications. The main takeaway from each technical article is summarized and categorized by manufacturing application and AI technique. The review also incorporated differing perspectives on certain applications of AI/ML in

FIGURE 1 (A) The technical articles used for this manuscript were grouped by their year of publication and the number of publications that were vetted from 2017 to 2021. This 2021 data was collected mid-year, so does not reflect the total count. (B) Word cloud displaying the 125 most common words among all references used. Results are out of a total of 67 different documents and 640 634 total words.

manufacturing to provide additional context for the challenges and benefits AI/ML has in manufacturing. For easy organization, each reference was summarized and tagged according to year (as illustrated in Figure 1A), location of publication, industry, AI technique, and manufacturing application. Voyant Tools,[10] a text analysis application, was used to provide an informal representation of topic prevalence among the reviewed literature targeted at AI/ML applications in industry, shown in the world cloud in Figure 1B. The relative sizes of each word in the word cloud provides a measure of the frequency with which they are encountered. It suggests the centrality of certain themes that combine elements such as data, learning, AI, systems intelligence, process, and research in manufacturing applications. The article count chart in Figure 1B provides a proxy indicator of the growing interest in AI/ML applications in manufacturing. This upward trend reflects a convergence of interests from both the research community and the manufacturing industry in exploring opportunities for leveraging AI/ML to improve value.

The manuscript is organized as follows: Section 2 provides a brief description of mature AI/ML algorithms and models which are used in manufacturing applications. Section 3 describes AI/ML applications in the manufacturing verticals such as operations, design, and automation. Section 4 describes the top four challenges encountered when trying to deploy AI/ML manufacturing applications within an existing manufacturing plant. Section 5 provides a brief description of the top four trends in AI/ML research and development which would aid AI/ML manufacturing applications, followed by conclusion in Section 6.

2 | AI PARADIGMS, TECHNIQUES, AND WORKFLOWS

AI is an umbrella term that encompasses a broad range of techniques and approaches, which has emerged as a major field in computer science. Almost all AI programs are meant for solving a single task for which it was specifically developed,[11] so, it would be apt to use the term artificial narrow intelligence (ANI) as opposed to AI. In earlier years, AI programs were mostly the so-called "expert systems." These were computer programs that mimicked expert human decisions for a given task. The expert knowledge was hard-coded into a computer program as a set of rules, based on which the program performed logical inference to provide an output that closely mirrors a human expert. Then came approaches based on heuristics, such as evolutionary algorithms, which discover solutions on their own while maximizing a performance metric. In recent years, AI systems based on ML, and specifically deep learning have gained popularity. These AI/ML systems need not be monolithic and may be comprised of several different techniques.

2.1 | Machine learning paradigms

ML refers to a set of algorithms and models that can learn to identify patterns and make decisions to solve specific tasks using data related to that task.[12] Software based on ML is developed by sourcing datasets that are related to the task (referred to as the training data), selecting a suitable ML model, and training the ML model to complete the task.[13] ML may be broadly classified into three main learning paradigms, namely supervised learning, unsupervised learning, and reinforcement learning. As shown in Figure 2, different machine learning models (techniques) may combine one or more of these learning paradigms for a given learning task. The relationship between learning paradigms, learning models, and tasks that is illustrated in Figure 2 is based on distilling the information from technical articles and author experience. A combination of learning tasks can be used to support a wide range of applications. Note that there is no single standardized approach for categorizing ML paradigms and techniques and alternative classifications exist.

2.1.1 | Supervised learning

In supervised learning, the ML algorithm is trained using data that has a set of inputs (features) and corresponding labels (labeled dataset). The labels might either be a discrete class or a continuous value. During training, the model learns to correctly predict the label associated with the input features. A trained model can then be used to predict labels for a new set of input features for which there are no labels.[14] Supervised learning is particularly useful for image, voice, and object recognition, and in general, for applications where large, labeled datasets can be obtained easily.

2.1.2 | Unsupervised learning

In unsupervised learning, the ML model is trained using only the input features with no corresponding labels.[15] The goal of training in unsupervised learning may be reducing the dimensionality of input features (e.g., Principal component analysis), clustering similar data points (e.g., k-means clustering), mimicking the training dataset (e.g., Autoencoders), or finding anomalous data points (e.g., Anomaly detection).[16] During training, the ML models for unsupervised learning discover hidden patterns in the data without the need for human intervention.

2.1.3 | Reinforcement learning

In reinforcement learning (RL), there is no pre-existing training dataset. Instead, an ML agent interacts with an environment and generates the training data which consists of observations (input features), actions taken by the agent when interacting with the environment, and a scalar value that captures the net benefit of agent actions (rewards). Here the environment refers to software that encapsulates the problem that we want to solve.[17] In reinforcement learning, the ML agent learns based on feedback from its environment. It takes action to explore its environment and transitions into a new state after every action. For each state, the agent receives a positive or a negative reward based on whether its action is desirable for the given state. As this process is repeated, the agent gradually learns to seek out positive actions and avoid negative ones and eventually determines an optimal (maximum-reward) path to its goal.[18–20] Unlike supervised learning algorithms, reinforcement learning does not need correct answers or targets to solve a given problem, it only needs information on whether an answer from the ML agent is in the correct direction. Reinforcement learning has useful applications in robotics, as well as optimization.

2.2 | Machine learning techniques

Machine learning techniques refer to the methods and algorithms that enable learning from data using one of the learning paradigms mentioned in Section 2.1. Most ML techniques are specifically suited for a single learning

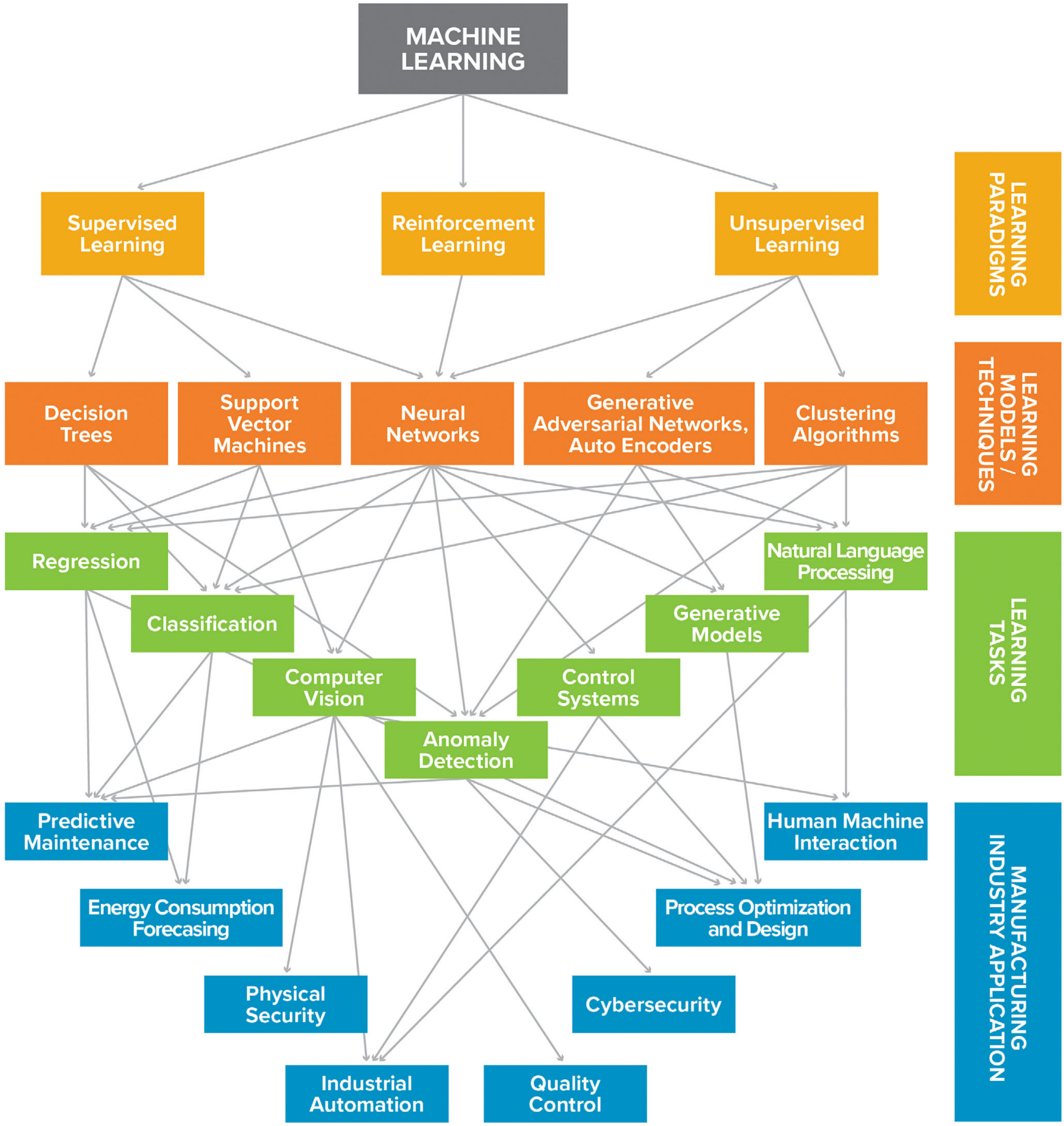

FIGURE 2 Common categories for various aspects of machine learning, grouped into paradigms, techniques, tasks, and relevant manufacturing industry applications.

paradigm. For example, decision tree models are exclusively used for supervised learning. However, a few models like neural networks can be used for learning all three paradigms. While multiple techniques can be used on the same types of problems, there are instances where one technique performs better than others. For instance, neural networks are better suited to computer vision problems while decision trees work better for regression on tabular data. In general, ML techniques can take multiple data types with multiple dimensions as input.

2.2.1 | Neural networks

Artificial neural networks (ANNs) are the most powerful learning model currently available and can be used for supervised, unsupervised, and reinforcement learning. They have a weak analogy to the network in the human brain formed by the biological neurons[6,21] and are comprised of connected layers of artificial neurons. Each neuron transmits the weighted sum of inputs through a nonlinear activation function (e.g., sigmoid, rectified linear) to produce an output that proceeds to the next layer of neurons.[22] An ANN with two or more layer of neurons is known as a deep neural network (DNN), which is more widely referred to as deep learning in both industry and academia. DNNs can be further classified into convolutional neural networks (CNNs), which apply a filter at each layer of nodes meant to observe a different feature and preserve spatial information; and Recurrent Neural Networks, whose nodes retain information from previous inputs and preserve state information.

2.2.2 | Decision trees

Decision trees fall into the supervised learning category and are a tree-like learning model of decisions that weigh decisions based on factors like consequences, likelihood, and associated costs. Decision trees are visual maps that represent the outcomes of related choices. They start with a single node—analogous to a root of a tree—that, for instance, represents a decision such as whether to make a sub-assembly of a product in-house or to outsource the assembly[23] and then branches into possible outcomes ("Yes" or "No" in this case) based on the weighted benefit of answers to that question.[24] These possible outcomes then lead to more nodes with each having its own distinct set of possibilities, giving it a tree-like structure. The tree is constructed such that the decisions taken within the tree lead to classifications that result in the least entropy. Decision trees are particularly useful because they allow users to quantitatively weigh the outcomes of actions based on parameters such as cost, benefits, and likelihood,[25] and can be supplemented with algorithms that objectively demonstrate the best action to take.

2.2.3 | Support vector machines

Support vector machines (SVMs) are a supervised learning method used for regression analysis and for the classification of data. They are discriminative classifiers defined by hyperplanes that divide a potentially large dataset into distinct classes or groupings of data.[26] SVMs, initially, generate a hyperplane onto a graph that contains all the data. This hyperplane acts as a line of separation that separates two or more classes.[27] The SVM uses an optimization algorithm to find the hyperplane that has the maximum margin, that is, the maximum distance between data points of the different classes. SVMs have the advantage of quickly classifying and categorizing data, which reduces the costs related to manually sorting the data.

2.2.4 | Clustering algorithms

Clustering algorithms are unsupervised learning algorithms that employ an iterative process to sort data into specific categories or groupings known as clusters based on the "nearness" (e.g., Euclidean distance) of the data points to a center of gravity. This machine learning technique is particularly useful for large sets of data as the resulting clusters can give rise to conclusions or previously undiscovered patterns within sets of data, which can be visually represented.[28]

2.2.5 | Generative adversarial networks

Generative modeling is an application of unsupervised learning to develop a probabilistic model that describes training datasets. Generative adversarial networks (GANs) have been one of the most successful learning models for generative modeling. GANS consists of two neural networks, a generator that learns from a training dataset to generate new data that could plausibly have come from the original dataset, and a discriminator, which evaluates whether the data point is from the original dataset or created by the generator. During training, the generator and discriminator try to outcompete each other until the generator starts producing more and more plausible results.[21]

2.2.6 | Scientific machine learning

AI/ML has found increasing use in the domain of scientific computing through an emerging field known as scientific machine learning (SciML). SciML is a data-driven approach that utilizes conventional ML models in combination with known physical laws for a given problem within a scientific domain.[29] SciML can be used to perform high-performance simulations that are several orders of magnitude faster than those using classical approaches. SciML utilizes the differential equations that define the known physics of a process while training the ML model. Their major use cases are (a) surrogate models which are orders of magnitude faster than classical models. (b) Parameterization of classical models using sparse measurement data.[30]

2.3 | Machine learning workflow

Developing a machine learning solution is an iterative process, hence, the software and hardware infrastructure (also referred to as the workflow) used to develop the solution is as important as the specific machine learning technique used. Figure 3 illustrates a high-level overview of a typical ML workflow. The relationship between different components of the workflow is based on software engineering and data science best practices and from the authors' own experience in implementing these workflows for AI/ML projects. The essential components of the workflow are (a) databases to store large amounts of data, such as those from industrial sensors; (b) an Extract-Transform-Load pipeline to preprocess and deliver data that can be used by an ML model; (c) the feature engineering pipeline for selecting features that give the best performance; and (d) the model development pipeline to define the train the AI/ML models. The feature engineering pipeline requires analysis of the data before model training and performing model validation after a trained model is available to perform down-select features for the AI/ML model. The model development pipeline requires modules to create an instance of the model (using an AI/ML software framework like TensorFlow) given the architecture and hyperparameters as input. It also requires hyperparameter optimization to find the hyperparameters which give the best performance. Finally, there is a need for sufficient computing hardware and software infrastructure necessary to train AI/ML models in a reasonable amount of time.

The traditional approach to implementing ML workflows is heavily manual, but AutoML (automated machine learning) technology provides a domain-agnostic way to automate repetitive tasks involved in implementing the ML workflow such as Extract-Transform-Load pipelines, feature selection, and hyper-parameter optimization.[31,32] These technologies create the potential to reduce the time and engineering cost of developing ML-based solutions.

3 | AI/ML APPLICATIONS IN MANUFACTURING

Current and emerging industrial applications for AI/ML techniques which play a crucial role in Industry 4.0 include optimization of manufacturing operations, process and product design, scientific machine learning, computational experimentation, and industrial automation. In Figure 4 we illustrate the scope of AI/ML applications in different manufacturing domains classified based on whether they are part of operations, design, or automation. Of these, process and product design are further along on the industrial demonstration and adoption curve, while real-time AI-driven automation and scientific machine learning are at an earlier stage of adoption. Overall, AI enables companies to gather and analyze copious amounts of data, identify patterns and insights, and automate processes, enabling faster and more informed decisions that improve operations and product development. This section will examine the objective, potential benefits, and challenges of AI strategies in manufacturing applications.

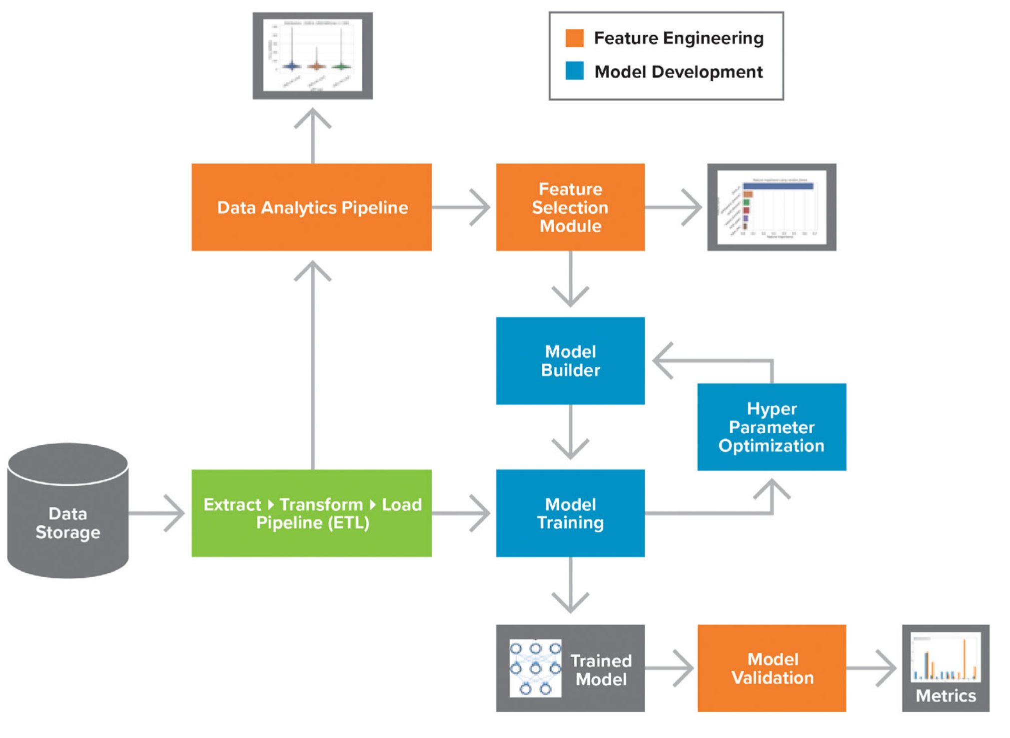

FIGURE 3 General workflow for developing the ML model for an AI/ML solution.

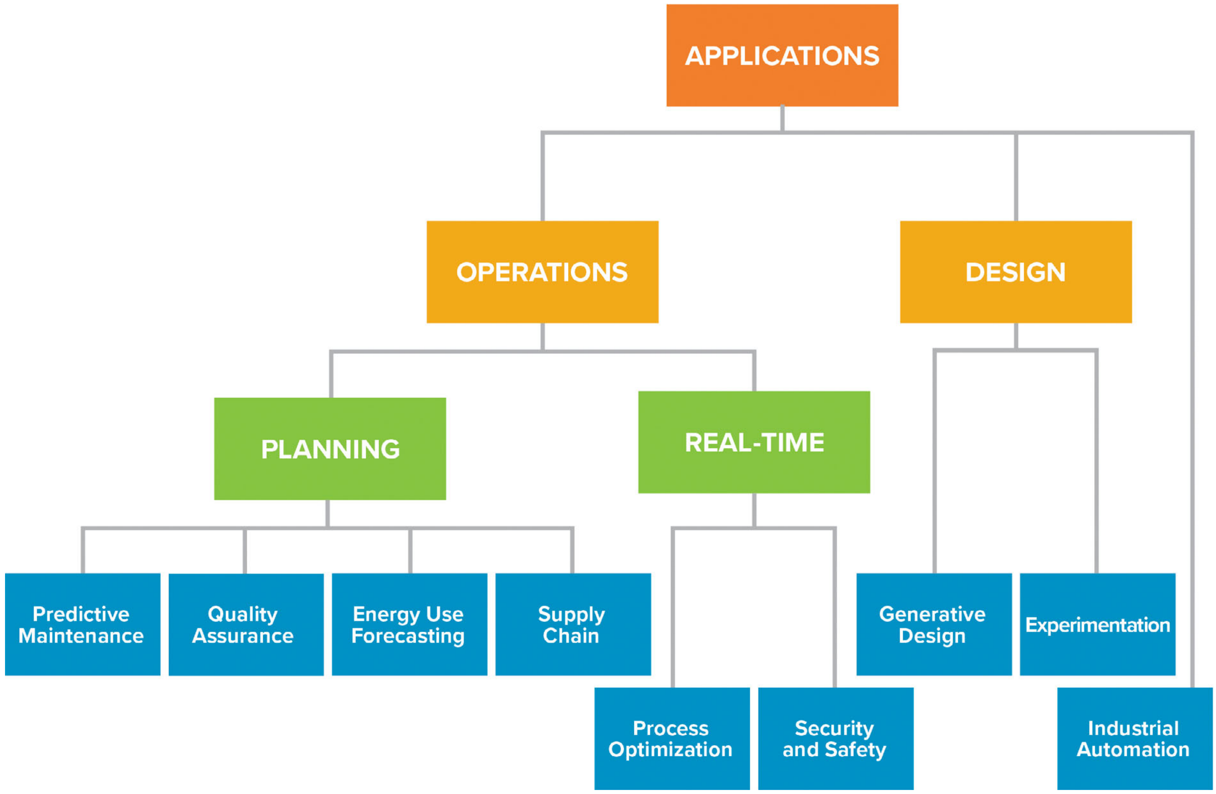

FIGURE 4 Representative AI/ML applications in the manufacturing industry.

3.1 | Operations

The term "operations" concerns the actual use of production facilities and resources.[33] On the physical side, it involves industrial machinery, sensors and controls, human workers, and facility infrastructure. More abstractly, it deals with logistics and processes, such as how exactly the necessary resources will be transported and manufactured into the final product. Operations may be classified as long-term plans for facilities and processes or real-time actions on the factory floor, depending on the relevant time horizon. They are critical to ensuring that industrial equipment is functioning as desired and product quality is maintained. Historically, human operators have exclusively managed operations. However, the predictive and analytic capabilities of AI/ML models can provide useful insights to human operators to facilitate planning, support real-time decision-making, and improve manufacturing efficiency and safety.

3.1.1 | Planning

a. Predictive maintenance

Predictive maintenance involves analyzing sensor data from equipment to anticipate potential equipment failures and scheduling maintenance routines to prevent unnecessary downtime. It is one of the most common uses for AI/ML in manufacturing industries, such as aerospace, chemicals, electronics, and consumer goods manufacturing.[5–7] The value to manufacturers is huge, as the ability to anticipate equipment failure can avoid significant material and financial losses by avoiding unscheduled disruptions and downtimes in manufacturing operations. Typical manufacturing facilities average 15 h of downtime a week, with losses of about $20 000 per minute of production line downtime for large automotive companies.[5] Predictive maintenance can also minimize risks of unplanned shutdowns to workers, communities, and the environment.[34,35] AI/ML strategies such as computer vision, regression, classification models, and anomaly detection can be directly applied to predictive maintenance to support factory floor error detection. Computer vision provides more detailed visual data than the human eye, and computers can observe factory operations for longer without interruption or fatigue. Using data from networked sensors, CNNs, ML-based computer vision models, and various supervised learning algorithms can be trained to predict equipment failure probability.[36,37] Regression models may be employed to predict the remaining useful life of a piece of equipment or estimate how much time it takes until the next failure. Classification models may be used to predict whether a piece of equipment will fail within a given time span. Predictive maintenance may also use anomaly detection to determine when equipment is behaving outside of normal parameters.[38,39]

b. Quality assurance

Quality assurance is essential to customer health and safety. Preventing quality failures can improve customer satisfaction, and reduce costs and waste.[5] AI/ML models have shown promise for augmenting quality control in a broad set of applications across manufacturing industries. Recent studies have shown that CNNs can match, and in some cases, outperform traditional methods for detecting manufactured product imperfection.[21,40] This is particularly important for additive manufacturing, where features such as density and porosity can have significant effects on the final product's mechanical properties.[40] In semiconductor manufacturing, computer vision models using CNN developed with the aid of AutoML were used to detect random defects in electron microscope images and wafer maps, which are important predictors of semiconductor performance.[31] These models have also been used on automotive manufacturing assembly lines to detect defects in LCD screens, optical films, and fabrics, with up to a 6% increase in detection accuracy.[31]

c. Energy consumption forecasting

Predicting the energy consumption of manufacturing processes is a proactive way of reducing environmental impact and improving sustainability. Using temperature, humidity, lighting usage, facility activity, and historical energy consumption data, regression models can predict energy consumption profiles at the facility and specific process levels. These can be exceptionally useful for energy efficiency and demand-response strategy, especially in energy-intensive industries such as mining and steelmaking,[41–44] as well as in additive manufacturing applications.[45] DNNs are particularly good at forecasting when historical time-series data from a large number of devices are available for training (e.g., smart energy meters).[46,47] SVMs are also suitable for short-term electricity consumption forecasting, especially when the forecasting problem involves a small number of samples (fewer historical data), and high dimensional inputs.[47]

d. Supply chain management

Supply chain management is one of the most critical tasks in a manufacturing operation and one of the most complex since supply chains can span multiple countries and continents. AI/ML can be used in applications that facilitate and optimize supply chains, leveraging predictive analytics and real time data analysis to manage their inventory levels and production planning.[48–50] AI/ML can use predictive analytics to forecast critical supply chain variables including (a) demand for a finished industrial product and (b) lead times for a critical component used to make that product. With real time data analysis, AI can provide valuable insights into market trends and conditions, helping companies to make timely decisions on purchasing feedstock or selling products in response to spot market signals. AI/ML-based predictive models can make use of far more historical data and features to provide predictions that are significantly more accurate than classical methods. Natural language processing (NLP) can extract valuable information from news feeds to provide market insights and digitize physical data—such as invoices—primarily meant for humans faster and more accurately than an unaided human data entry operator. Industry robots and drones using computer vision based on AI/ML models can operate within a warehouse with minimal supervision and an unprecedented level of accuracy. They can be used to both keep track of inventory and aid in recovering items from inventory.[51] Other applications include tracking and reducing wastage, real-time monitoring during logistical operations,[48] as well as automation of routine tasks to reduce errors and improve productivity. RL has also been used to streamline production pathways and for scheduling to minimize delays and optimize productivity.[52]

3.1.2 | Near real-time operations

a. Process optimization

Historically, optimization has been applied to individual manufacturing processes as well as larger-scale operations such as facility layout and supply chain management. The increasing diversity and complexity of manufacturing tasks, workflows, and supply chains has increased the number of variables and interdependencies. Manually finding an optimal solution via experimentation is time- and resource-intensive, and the effectiveness of current mathematical approaches such as heuristic or model-based optimization decreases as the number of variables and interdependencies grows.[18,43,53] AI/ML techniques have emerged as supplements or comparable alternatives to classical optimization algorithms for manufacturing processes and procedures.[5,40] Examples include RL for hydrometallurgical separation process design optimization,[18] and hybrid support vector and evolutionary algorithms for multi-objective optimization, which was applied to a carbon fiber manufacturing process to realize a 45% reduction in energy consumption.[43]

AI/ML may also be used to optimize larger-scale processes such as factory layout design, inter- and intra-facility dispatch management, and logistics. Recurrent Neural Networks have been used to optimize delivery and dispatch services by autonomous guided vehicles while avoiding conflicts with workers or other vehicles.[54] RL has also been used to optimize dispatch within a facility[20] (such as a factory floor or warehouse), and for job-shop scheduling—where one product requiring several tasks which must be completed on separate machines while ensuring an optimal layout of equipment.[55] Other use case applications for RL include improving the ability of robots to identify and pick out an object from specific bins,[56] select the best paths to minimize unnecessary stops, and avoid obstacles and interference with human operators.[57] It is also becoming more common to see hybrid applications where machine learning techniques are integrated with classical optimization techniques and process simulation.[58]

Digital twins represent another application where AI/ML can have significant impact on manufacturing, with a 2020 case study reporting significant benefits from the use of digital twins in large scale smart manufacturing operations.[59] Digital twins are virtual replicas of a manufacturing unit or facility within a simulated environment. One major value proposition of AI/ML-based digital twins is that they provide several orders of magnitude reduction in simulation time over conventional approaches, which makes it feasible to use them for real time data analysis and process control. They can also be used to conduct experiments and to test minor changes to system design, allowing operators to evaluate potential process responses and behaviors before actuating an updated control logic on the factory floor. AI/ML based digital twins may also assist with automation to enable intelligent and autonomous manufacturing.[60,61]

b. Security and safety

AI/ML can also improve worker and critical equipment safety within factories through intelligent access control systems. It can also be used to mitigate the cybersecurity risks introduced by the ever-increasing number of networked devices within a manufacturing plant. Computer vision based on deep learning can visually identify unsafe behaviors for employees and identify the presence of unauthorized personnel within a facility.[62–64] A study of process manufacturing in the chemicals industries used deep learning to examine the relationships between process factors to predict potential accidents[65] For industrial cybersecurity, AI/ML models are used in intrusion detection systems[66] by detecting anomalous patterns in user behavior or network traffic such as, for example, analyze a program's sequence of system calls to evaluate whether it is malicious or not.[67] Unsupervised learning models may be combined with expert systems for anomaly detection, as data generated by operational technology is predictable. GANs can be used to generate data that can model the relationship and information flow between cyber and physical systems, using the information to determine whether security requirements are met.[21]

3.2 | Design

Design involves developing new or modified products and processes, modeling them either digitally or physically, and testing them to ensure they are feasible and meet the manufacturer's goals. The typical design process for manufacturing is iterative, requiring tests of each new design to determine its effectiveness, and requiring process designers to expend considerable time, labor, and materials while iterating towards an ideal result. Emerging AI/ML techniques for aiding process/product design include predictive modeling, generative design, and reinforcement learning. AI/ML-based predictive models provide significant productivity leverage to product designers,[68] and when coupled with AutoML to simplify the predictive analytics workflow, speed up implementation while avoiding drawbacks in the traditional approach due to costly experiments and time-consuming simulations. Currently, NVIDIA (through the Omniverse platform) and ANSYS (through the Twinbuilder tool) provide some of the most powerful design tools that utilize by AI/ML models.[69,70]

3.2.1 | Process and product design

Generative design involves the use of AI to explore the design space for a product or process based on user-provided requirements. To achieve this, the AI is first trained on a large corpus of existing designs. New designs are then generated by interpolating or sampling within the space. This approach permits a wide variety of design options to be explored in a shorter amount of time. The human designer can then focus on selecting from the generated design alternatives.[71] Generative models can also be repurposed to make modifications to an existing product design to enhance customization, improve performance, or adapt to new situations.[72] GANs are the most popular because of their ability to generate high-grade image data consistently and allow for multi-modal inputs[73] and may be applied to generative design. GANs are most effective when training data is available, and a basic idea for the design is already known (e.g., developing new models of cars in the same segment[5,21]). Reinforcement learning has been used for performance-optimized layouts for computer chips, given density and congestion constraints.[19]

SciML has been used in fluid mechanics modeling and was shown to reduce the computational time required to solve these higher dimensional Partial Differential Equations, allowing designers to iterate faster.[74] In one study, a fluid mechanics-based model of a 2D nozzle design was simulated using a surrogate SciML model, saving significant labor and expenses otherwise needed for the traditional approach that requires multiple design iterations involving computationally intensive simulations.[75] SciML can be used to speed up solving optimization problems in cases where optimization algorithms need to solve a Partial Differential Equations at every iteration.[76]

3.2.2 | Experimentation

AI and ML can be used for high-fidelity simulations of manufacturing processes and to reduce the need for manual experimentation which saves cost and time. This is especially beneficial in situations where the process or experiment is complex or expensive. ML models can simulate experiments, optimize independent variables, and predict outcomes with accuracy comparable to traditional experimentation. For instance, techniques such as Bayesian optimization have been used to develop autonomous experimentation systems to perform mechanical testing of additive manufacturing structures towards identifying best-performing configurations for different applications, and achieved a 60-fold reduction in the number of experiments needed.[77] Hybrid AI/ML workflows integrating statistical methods, machine learning surrogate modeling, and Bayesian optimization have also been used successfully in design of experiments for applications such as nanomaterial production via flame spray pyrolysis, where it reduced number of in-situ particle size measurements and improved particle size distribution in the product.[78] Similar success was reported for a bioprocess development study that combined design of experiment with surrogate modeling using DNNs.[79] ML experimentation involving a range of supervised and unsupervised ML techniques has been used successfully in advanced materials development to examine how various substances will behave under extreme heat and pressure[80–82] and to reduce costs and development time for additive manufacturing processes for high-strength light-weight alloys in aerospace components.[83] These studies show that different learning approaches can play complementary roles. For instance, unsupervised learning can filter trends in the data that model underlying behavior/properties, simplifying datasets ahead of more complex, detailed treatment with supervised learning to inform material selection.[82]

3.3 | Automation and human–machine interaction

Industrial robots are already a mainstay of modern manufacturing. Incorporating AI into existing industrial robots has the potential to facilitate a step change in the cooperation between human workers and robots. It could allow robots to quickly adapt to variable human behavior to maintain safety and efficiency. AI/ML can assist with shortages of human expertise by enabling robots to copy expert human behavior. This can be achieved by using supervised learning techniques to train an ML model to imitate the decision-making skills of experts. A 2018 study on using deep reinforcement learning for automating water purification plants proposed combining supervised learning with RL for greater versatility—allowing the agent to both refer to a "manual" of information and make experience-based decisions.[84] Other studies have also shown that AI/ML can enable robots to perform tasks such as support removal in metal additive manufacturing,[85] or autonomous vehicle management[54] that were dangerous or tedious for humans while being too complex for conventional robots. Human flexibility is still a necessity in manufacturing, and as AI for industrial robots becomes more common, human-machine interaction becomes unavoidable. It is necessary to examine methods of facilitating these interactions and permitting machines to adapt to the nuances of human behavior. This may come in the form of NLP—for example, developing a language database and then applying a recurrent neural network to understand verbal complaints and assist with maintenance or repair.[86] It may also involve RL as a tool for allowing industrial robots to observe the state of the factory floor and take actions corresponding to the need.[87]

4 | CHALLENGES

Incorporating AI/ML into manufacturing involves several challenges in the areas of data acquisition, energy consumption, implementation, security and privacy, and decision validation. Figure 5 illustrates some of these broad challenges and their underlying causes. The rest of the section discusses their implications for implementing AI/ML in manufacturing.

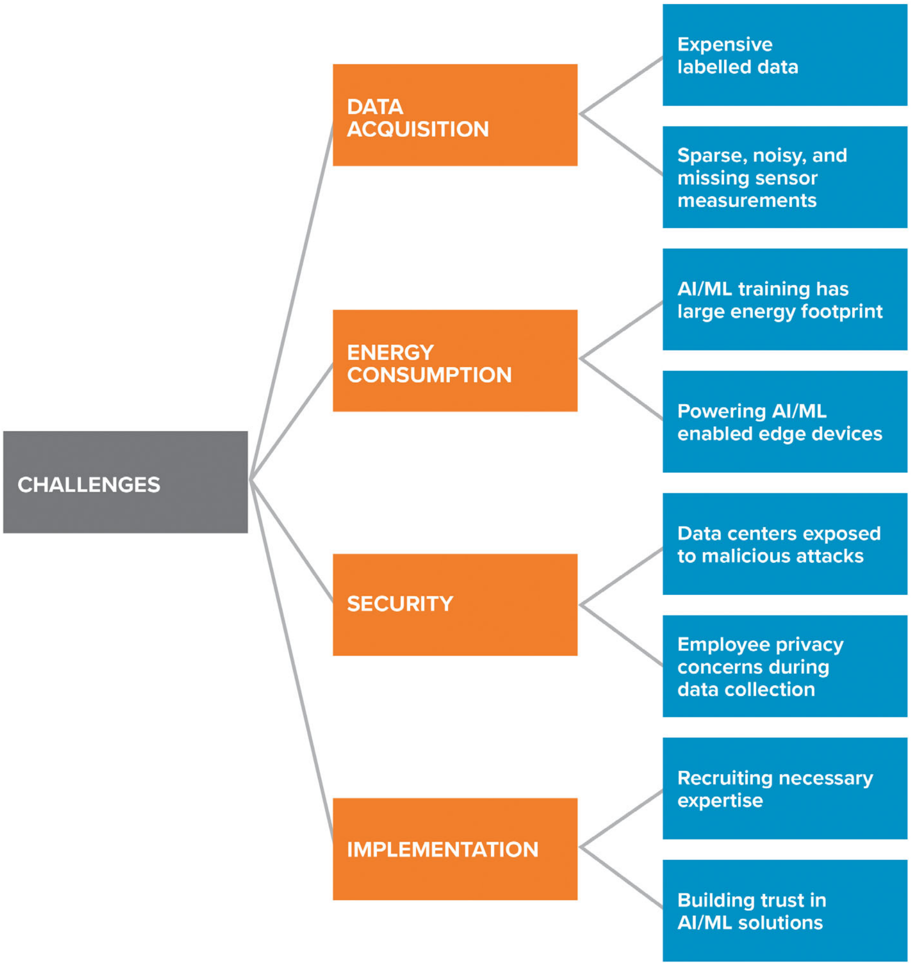

FIGURE 5 A high-level illustration of the challenges involved in implementing AI/ML solutions within the manufacturing industry.

4.1 | Data acquisition

Large amounts of data are required to train supervised and unsupervised learning models. Acquiring any kind of data from the premises of an industry can be challenging because of the proprietary nature of manufacturing equipment and units. In addition, interfacing with servers in the plant control room would also require security clearances which plant managers and operators may be reluctant to provide. Any data acquired from the industry will require a significant amount of preprocessing before it can be used to train an AI/ML model. Labeled data will be even more costly due to the expertise necessary to label the data, and the time required to do so. Additional challenges include the rarity of certain events of interest such as equipment breakdowns, difficulty of interfacing between disparate sensors,[88,89] and the impact of production conditions on measurements. Exposure to varying or extreme manufacturing environment conditions like heat release, robot motion, and pressure can affect sensor output, and over time, can lead to sensor drift which may bias collected data.[53] In addition, taking frequent measurements can be costly, in part due to the associated cost of data storage and transfer which in 2016 was estimated at $3351 on average for storing a terabyte of data for 1 year.[90]

4.2 | Energy consumption

Developing AI/ML-based solutions requires training models that require moving large quantities of data (i.e., memory transfer) and large computing operations (e.g., high dimensional matrix multiplication) at each step of a training run. Large training runs can take multiple days or weeks and require significant amounts of energy—most of the energy used with respect to AI/ML models is during training—and consequently, emissions if non-renewable energy sources are used. Since 2012, the computing power used for training AI/ML models has doubled approximately every 3.4 months.[91] A 2021 study on AI-powered analytics for manufacturing reported that the carbon emitted during the training of a DNN-based NLP model was about 60% of what a single average car produced over its entire lifetime.[51] While energy consumed during inference is orders of magnitude less than that during training, a study on energy computing trends reported that the average energy consumption to perform one inference step in DNNs increased from 0.1 to 20 J during the period from 2012 to 2022.[92] Hence energy-intensive AI models can have consequences for the environment. Assessments and conclusions from multiple studies suggest that to significantly integrate AI/ML-based solutions, manufacturers face a trade-off between complex, detailed algorithms that provide high levels of accuracy on the one hand, and the need to reduce training time and consequent energy consumption on the other.[40,51,66,82,88,93]

4.3 | Security and privacy

Developing AI/ML applications requires accessing data on servers (historians) located within plant control rooms. There is a potential for malicious actors to use this opportunity to engage in cyberattacks on industrial control systems which would result in large financial costs as well as safety concerns due to possibility of serious equipment malfunctions.[66] In 2020, the global average cost of a data breach was reported at $3.86 million.[94] In 2021, an IBM report estimated the global average cost at $4.35 million, with the United States average closer to $8.5 million.[95] While general cybersecurity solutions are also available,[66] and the deployment AI security solutions can potentially reduce the cost of data breaches by up to 70%,[95] the nature of threat advancement means this problem is always changing and requires constant adaptation. Research into safety systems and human-machine interaction involves using human data and monitoring employees and there is a debate concerning employee privacy.[87] Data involving employees must be kept secure and anonymous and applied in a way that respects their rights. Additionally pre-processing should be applied to key performance variables such that bias is removed.

4.4 | Implementation

Implementing AI solutions, including using mature AI/ML technologies remains challenging. There are difficulties with establishing a foundation of infrastructure and personnel, limited consideration of the interrelationships between the complex human and technical systems affected, or discrepancies between the most accepted solutions and the solutions that work best in a particular setting. Lastly, the manufacturing industry practices have been built upon on decades or even centuries of human experience on the factory floor. Many of these practices still exist because they are tried-and-true, and not necessarily because they are the most efficient. Consequently, there is no guarantee that any AI/ML based solution—no matter how efficient—will be readily accepted on the factory floor, especially if it requires radical changes to existing industry practice. A 2019 survey of 250 manufacturing professionals analyzed the challenges industries have faced when implementing AI and identified difficulties in establishing a clear industry-specific implementation plan.[9] According to the survey responses, pressure from within the industry to use AI has contributed to companies feeling obligated to pursue AI/ML solutions even when they lack a concrete plan. Moreover, AI/ML is often deployed in isolated, specialized situations, and thus does not pick up contextual information that could benefit the process further.[96]

Moreover, every AI/ML solution for a given manufacturing problem has its risks and benefits and it differs across companies, across applications, and across specific instances of said applications. For instance, a study on AI-powered real-time analytics for manufacturing compared three ML-based approaches to solving the problem of product collisions on a conveyor belt.[51] The first, a classification algorithm using classical ML approaches for video data, was easy to implement but lacked adaptability for situations that did not resemble the sample footage. The second, a CNN trained to classify objects as "together" or "apart" and alert operators if objects were "together" for too long, was fast but not generalizable. The third approach used two CNNs in succession, tracked multiple objects on the product line, and transferred information between frames about product position and velocity relative to other products. This was accurate but required heavy computational power and a long time to train. Thus, in general, the choice of which AI/ML solutions to implement for specific manufacturing problems is not always trivial and involves a certain degree of trade-offs. Manufacturers must be able to decide what drawbacks they can afford when implementing AI.

4.5 | Decision validation

Decision validation plays a key role in the consideration of AI/ML for manufacturing. The lack of interpretability of the outputs from the AI/ML model makes it difficult to use for planning considering that the human, environmental, and financial costs of failure in a manufacturing operation may be significant. Determining the trustworthiness of decisions made by AI/ML is a topic of ongoing research, particularly since ML models typically take the form of black boxes. Historically, human operators gradually learn how much trust to place in new software technologies after observing outputs from these systems over time and it would be expected that the same would be true for AI/ML applications.[96]

5 | AI/ML TRENDS AND OPPORTUNITIES IN MANUFACTURING

The literature that was surveyed in the previous sections suggests that currently, AI/ML-based solutions supplement human labor rather than provide complete automation. This is further corroborated by the survey done in Wee[97] which found that 38% of manufacturers use AI for operations related to business continuity, 38% use it to help employees be more efficient, and 34% found it to be helpful for employees overall. In the opinion of the authors, we may be currently witnessing a gradual process whereby manufacturing industries steadily develop trust and experience with AI/ML solutions starting with high-level analytical tasks and ending with automation on the factory floor. We illustrate this gradual development in Figure 6. Hence, AI/ML solutions that allow companies to experiment with AI/ML with minimal risk (e.g., obtain high-level analytics useful for plant operators on existing processes generating copious amounts of data) would be most sought after. Applications that support decision-making, such as design and optimization algorithms would be the next solutions of interest. Finally, AI/ML solutions that directly integrate with the automation and robotics on the factory floor would be implemented after a significant level of trust has been generated and in-house expertise created. In addition, the AI/ML-based analytical and decision-support support applications should have demonstrated measurable value.

In terms of fundamental AI, research and development, there are four areas where advances would benefit AI/ML solutions in manufacturing and overcome the challenges mentioned in the previous section. First, high quality synthetic data suitable for training AI/ML models or augmenting existing sparse datasets can be obtained using generative models like GANs,[21,98–100] to compensate for smaller quantities of data from manufacturing operations. This technique cannot extrapolate or generate results beyond the extremes of its training data. But it is low-risk and addresses a challenge of providing anonymized data to train AI/ML models.[100] Researchers have used DNNs to deal specifically with sparse functional data.[101] An architectural framework to unify data acquisition from disparate networked industry devices, signal processing, and analysis within a robust interface was presented in Serizawa and Shomura.[89] Second, improving the FLOPS to Watt ratio (i.e., energy efficiency) of AI/ML hardware accelerators will translate to lowering the capital cost incurred in both developing and deploying AI/ML solutions in manufacturing. Another approach is reducing the size of trained models. In Ding et al.,[61] the efforts to develop a framework for reducing memory use in a variety of DNN architectures are described by removing unused parameters which reduced memory by 96% and computation by 90%. Third, improving the computing and communication capabilities of edge computing hardware (e.g., Jetson NANO which can run AI/ML models for applications like image classification, object detection, segmentation, and speech processing[102]) can accelerate the deployment of AI/ML solutions on the factory floor by removing the need to run AI/ML models on a server.[103] Fourth, building trust in decisions from AI/ML decisions through the concept of Explainable AI,[104] which involves working to develop a formal decision confidence measure for AI, to improve interpretability by humans. This provides human operators with more detailed information to determine whether to trust a decision made by AI/ML. Another concept is that of "humble AI"[105] that can understand its limitations and revert to a default, safer state of behavior if it is uncertain about its situation or competence. Another approach to improve explainability of AI predictions is the use of easy-to-understand graphs to interpret decisions from AI/ML models. For instance, a study on equipment health indicator

FIGURE 6 The progression of AI/ML solutions for manufacturing as trust in AI grows. The arrows at the bottom represent proximity to the factory floor for each application, with analytical tasks being the farthest and automation being nearest.

TABLE 1 Challenges and opportunities for AI/ML in manufacturing.

Challenges	Research opportunities
Data paucity: Obtaining sufficient data is expensive	Generative models, transfer learning
Data privacy: Industry data is sensitive	Edge computing, generative models
Energy consumption: Large AI/ML models tend to have higher performance but training large AI/ML models is energy intensive	Energy efficient AI/ML models
Implementation: New workflows introduced by AI/ML applications may not be readily accepted	Edge computing, large language models
Decision validation: Higher level decisions from AI/ML applications may not be trusted	Explainable AI

learning with DRL developed a time-based graph correlated with system health and operating conditions to address the black box concern in predictive maintenance algorithms.[38] Table 1 summarizes the challenges and associated research opportunities for improving the adoption of AI/ML techniques in manufacturing.

6 | CONCLUSION

The rapid evolution of AI/ML technologies offers an unprecedented opportunity to transform the manufacturing industry. This review covered a broad range of manufacturing applications, detailing the potential of AI/ML to improve the safety, efficiency, productivity, and sustainability of manufacturing. It examined applications, potential benefits, and challenges of integrating AI/ML in the manufacturing pipeline, including operations, planning, quality assurance, energy consumption forecasting, process optimization, security and safety, product design, automation, and human-machine interaction. Consequently, the review identified nascent developments, current challenges, and future directions in AI/ML relevant to manufacturing, highlighted AI/ML technologies available for solving manufacturing problems and identified areas where further research can yield transformational returns for the industry.

AI/ML can leverage the large amount of data generated from industrial sensors to derive actionable insights as well as take optimal actions independently. AI/ML models can improve over time as the data, infrastructure, and algorithms are iterated upon and provide compounding benefits to the manufacturing industry over the next decade. At the same time, the AI/ML solutions also require a thorough understanding of the possible trade-offs involved (e.g., restructuring facilities, energy costs, and expertise) and the specific needs and capabilities of the company and stakeholders. The trends indicate that AI/ML will continue to be applied cooperatively, alongside human skills, while at the same time gradually increasing the amount of automation. The rapid evolution and advancement of AI/ML algorithms and techniques will drive adoption in manufacturing industry applications, to the extent that they keep demonstrating improvements in safety, product quality, and operational efficiency. With the increasing adoption of AI/ML in industry, trust in the efficacy and productivity potential of this technology will grow across industrial sectors and among practitioners. However, the rate of adoption will be constrained by the associated risks, especially as the application moves from analytical support to AI control of industrial operations. AI/ML implementation decisions must be suited to each company's unique situation and needs and in the future, this field would benefit from longer-term case studies of manufacturers that have adopted AI/ML versus those that have not.

NOTATION

AI	artificial intelligence
ANI	artificial narrow intelligence
ANN	artificial neural network
AutoML	automated machine learning
CNN	convolutional neural network
DL	deep learning
DNN	deep neural network
DRL	deep reinforcement learning
FLOPS	floating point operations per second
GAN	generative adversarial network
IoT	internet of things
ML	machine learning
NLP	natural language processing
NN	neural networks
RL	reinforcement learning
SaaS	Software as a Service
SciML	scientific machine learning
SVM	support vector machine

AUTHOR CONTRIBUTIONS

Siby Jose Plathottam: Conceptualization (equal); methodology (equal); supervision (equal); validation (equal); visualization (lead); writing – original draft (lead); writing – review and editing (lead). **Arin Rzonca:** Data curation (equal); formal analysis (supporting); investigation (supporting); visualization (supporting); writing – original draft (supporting). **Rishi Lakhnori:** Data curation (equal); formal analysis (supporting); investigation (supporting); visualization (supporting); writing – original draft (supporting). **Chukwunwike O. Iloeje:** Conceptualization (lead); methodology (lead); project administration (lead); supervision (lead); validation (equal); writing – original draft (equal); writing – review and editing (equal).

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The authors declare no competing interests.

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Data sharing is not applicable to this article as no new data were created or analyzed in this study.

ORCID

Siby Jose Plathottam https://orcid.org/0000-0003-4813-5724
Chukwunwike O. Iloeje https://orcid.org/0000-0002-3426-9425

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