

Intelligent Automation Using Artificial Intelligence for Enhancing Operational Efficiency in Manufacturing Startups

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Abstract

The research study delves into the ways in which entrepreneurs are utilizing the manufacturing processes using Artificial Intelligence (AI) strategically. Modern manufacturing is challenged by unpredictable downtime, quality deviations and resource inefficiencies. This is due to rising global competition, the demand for mass customization and the inherent complexities of Industry 4.0. Moreover, the sheer volume of operational data generated in ever more complex production environments challenges modern manufacturing startups. Traditional optimization approaches are generally static and reactive, and thus inadequate in such dynamic environments, and a paradigm shift towards intelligent and data-driven solutions is needed. This research was carried out with a qualitative and descriptive research design, which was based on an extensive secondary literature review that systematically analysed and included academic journals, conference papers, industry reports and specialized books. The key findings show that AI is a disruptive technology that drives the advent of Industry 4.0 and Industry 5.0 in manufacturing startups and enables the creation of smart factories and highly agile production systems. AI has a holistic impact, optimizing processes along the entire manufacturing value chain, from predictive maintenance and smart quality control to flexible production planning, resilient supply chain management, energy efficiency and advanced robotics. This widespread adoption of AI brings tangible benefits such as a significant improvement in OEE, a substantial reduction in operating costs, enhancement of product quality, shortening of lead times, improvement in safety and sustainability. The research highlights the importance of data-driven decision making by entrepreneurs and the strategic shift to edge computing for real-time insights. Despite these advances, the research identifies persistent technical challenges for manufacturing startups (e.g., data quality, legacy integration, lack of AI certification, need for Explainable AI), organizational hurdles (e.g., talent gap, resistance to change, unclear ROI), and ethical/social considerations (e.g., job displacement fears, algorithmic bias, trustworthiness). Managing these complexities successfully relies heavily on a range of enablers, such as technological advances, proactive organizational strategies, and a supportive external ecosystem, guided by a proposed phased implementation framework. The research ultimately points to an increasing human-AI symbiosis in manufacturing startups, where AI enhances human capabilities.

Keywords: Artificial Intelligence, Entrepreneur, Explainable AI, Industry 5.0, Manufacturing, Startup

1. Introduction

The present-day industrial environment is in the midst of a profound redefinition, driven by intensifying global competitive pressures, a growing demand for customized product solutions, and the inherent limitations of conventional operational models (George, 2024). Traditional paradigms for manufacturing optimization based on

static methodologies and reactive responses are increasingly inadequate to deal with the fluid and data dense environments of modern production (Singh *et al.*, 2025). The current research study is an attempt to explore in detail the transformative role played by artificial intelligence (AI) in refining manufacturing processes of startups. The present study aims at providing a holistic understanding of the burgeoning potential of AI, its practical deployments and the pivotal determinants that influence its successful organizational integration by new age entrepreneurs.

Modern manufacturing processes have reached an unprecedented level of complexity driven by several forces. The industries are being forced to change constantly by fierce global competition, a strong focus on highly customizable products (*including “lot-size one” production*) and the need for more speed and less overhead (Wolf and Lepratti, 2020). This leads to complex networks of production and logistics processes, which require high planning, operational, quality and security standards. However, this escalating complexity presents significant challenges for manufacturing startups. They are continually asked to cut costs, raise the quality of their products and speed up production while cutting back on waste and reducing energy usage. Today’s production environments are dynamic and unpredictable, with events such as supply chain disruptions, machine breakdowns and quality deviations occurring frequently (Vital-Soto and Olivares-Aguila, 2023). Continuous monitoring, inspection and adaptation are required to maintain stable operations and consistently high product quality.

Manufacturing optimization has been traditionally based on lean manufacturing, Six Sigma, total quality management, materials requirement planning (MRP) and enterprise resource planning (ERP), etc. Lean principles focus on eliminating waste and maximizing efficiency. Six Sigma emphasizes reduction of variation in processes and quality improvement. MRP and ERP systems manage resources, planning and operational processes throughout the enterprise. These traditional techniques although provide significant improvements, have difficulties to adapt to the current highly dynamic and complex environments (Vital-Soto and Olivares-Aguila, 2023). They often struggle to provide the real-time adaptability and deep insights required to manage unpredictable events, volatile supply chains and rapid product changes (Singh *et al.*, 2025). Their static or periodically updated models are not capable of properly reacting to continuous, unforeseen variations or extracting meaningful patterns from the large volumes of data generated by modern smart factories (Wolf and Lepratti, 2020). The gap indicates a need for more sophisticated optimization methods.

The methodological framework of this research study is a qualitative and descriptive research design, presenting a broad literature review of the academic and industrial literature. It is a systematic interrogation of documents such as peer-reviewed journals, conference proceedings, sector-specific reports and seminal texts. Sophisticated AI tools acted as a crucial cognitive aid, substantially improving the research process by enabling nuanced interpretation of content, comparative analyses, and recognition of recurring thematic elements, thereby facilitating comprehensive synthesis of voluminous information sources.

AI is one of the most important forces driving the transformation of manufacturing into the Industry 4.0 and Industry 5.0 eras (Rijwani *et al.*, 2025). It serves as a key enabler of intelligent production facilities and adaptive ecosystems that go beyond automation to achieve autonomous and responsive intelligence (Kaur, 2025). It has delivered benefits across the value chain from product design and core production to supply chain management, quality assurance, predictive maintenance, energy optimization and advanced robotics with higher overall equipment effectiveness, lower costs in maintenance, energy and materials, better product consistency, faster market response, improved safety, sustainability and organizational resilience (Rijwani *et al.*, 2025).

These developments are based on data-centric operations with edge computing playing a key role in enabling real-time analytics and autonomous decision making close to the data sources. The integration of AI into manufacturing is not without its challenges, including data integrity, legacy system integration, a lack of explainable AI and immature certification frameworks (Rozhok *et al.*, 2025). Organizational challenges in startups, such as talent gaps, inertia, difficulties in quantifying return on investment, and disjointed data approaches, further complicate AI adoption. Overcoming these challenges requires advanced technologies, visionary leadership, robust strategies, and external support in the form of research collaborations, government incentives and industry standards (Kaur, 2025). The study offers insights into the evolving human–AI partnership in manufacturing startups, which augments human capabilities but requires ongoing workforce adaptation and ethical directions, with benefits that extend beyond large industries to SMEs in developing contexts.

From a strategic leadership perspective, manufacturing executives need to integrate a well-defined AI strategy into enterprise goals, supported by a strong digital infrastructure, including resilient industrial internet of things (IIoT) systems, scalable data storage, advanced edge processing, and strong cybersecurity (Kaur, 2025). Equally critical is workforce transformation via continuous upskilling, cultivating a collaborative human-AI culture and embedding proactive risk governance to address technical, operational and ethical challenges (Rijwani *et al.*, 2025). Finally, AI adoption should be iterative, beginning with specific pilot projects and evolving continuously for flexibility and long-term viability (Westover, 2025). In conclusion, AI is a strategic imperative for modern manufacturing, driving efficiency, resilience and sustainable growth while securing future competitiveness. Manufacturing startups should adopt AI in phases, focusing on data readiness, talent development, and ethical implementation. Policymakers and educators must facilitate this transformation by providing regulations, supporting interdisciplinary research, and building strong talent pipelines. This research offers important insights for organizations to harness the full potential of AI in the future of global manufacturing.

2. Background

Modern manufacturing processes are embedded in an increasingly complex and dynamic global landscape, marked by fierce competition, rapid technological progress and a growing demand for highly customized products (Wolf and Lepratti, 2020). Traditional optimization methodologies (e.g. Lean, Six Sigma, etc.) have historically resulted in significant gains, but often do not account for the inherent complexities and real-time variability of modern industrial environments (Vital-Soto and Olivares-Aguila, 2023). They are not enough because they have limited capacity to process a lot of data from different sources and react fast to unexpected changes (Singh *et al.*, 2025). Today, the greatest challenge for manufacturing startups is the battle to achieve the optimal performance in the face of increasing operational complexity and unanticipated disruptions (Wolf and Lepratti, 2020). In particular, the manufacturers are faced with the following:

Equipment failures and downtime: Equipment breakdowns can occur unexpectedly and lead to significant production losses, increased maintenance costs, and delays in delivery. Traditional methods cannot provide the continuous, accurate monitoring necessary to track equipment degradation from possible to catastrophic failure.

Inefficient planning and suboptimal resource allocation: Manual or static systems for managing large resources, complex production schedules and unstable supply chains often lead to inefficiencies, bottlenecks and the suboptimal use of materials and energy. The problem includes disruption problems in inbound logistics that affect the availability of critical materials.

Quality defects and ineffective inspection processes: High throughputs make it difficult to meet stringent quality demands. Traditional visual or rule-based inspection techniques are often unreliable, expensive, error-prone and difficult to scale. This leads to defects going undetected, or excessive material waste due to over-rejection.

Energy inefficiency and sustainability issues: Production operations consume a lot of energy and their impact on the environment is an increasing problem. Real-time optimization of energy consumption is a major challenge, especially with variable energy sources, which impacts on cost competitiveness and sustainability goals.

Safe human-robot collaboration in challenging environments: As collaborative robots become more widespread and more sophisticated machinery is introduced by manufacturing startups, the need for robust detection and avoidance systems is becoming critical to ensure worker safety in dynamic and unpredictable industrial settings.

Handling explosive data growth: Modern smart factories are overwhelmed with data from pervasive IoT devices and sensors that produce mind-boggling volumes of real-time, diverse data. The sheer volume and velocity of this data are too great for traditional analytical tools to glean actionable insights, spot underlying trends or make informed, real-time decisions.

The complexity of these challenges exposes a major gap in the current operational frameworks of manufacturing startups, which cannot fully leverage the huge amount of data generated for truly adaptive, proactive and resilient

manufacturing processes. This requires a paradigm shift towards intelligent solutions capable of handling complexity, transforming raw data into actionable knowledge and enabling self-optimizing systems (Rozhok *et al.*, 2025). Based on the challenges described and the disruptive potential of AI for the current industry, this research aims to study the optimization of manufacturing processes by the use of AI in a systematic way. The main goal of this research work is to give a broad summary of AI's potential to solve manufacturing challenges and to provide tangible recommendations to manufacturing startups. The specific research objectives of this study are:

Objective 1: Understand current state and future development of manufacturing optimization, emphasizing the shift from traditional approaches to advanced data-driven methods enabled by state-of-the-art technologies.

Objective 2: To investigate and classify different AI techniques and their particular importance to the various aspects of the manufacturing processes including but not limited to machine learning, deep learning, computer vision and reinforcement learning.

Objective 3: To explore and critically evaluate the benefits and potential challenges of AI integration in various manufacturing processes from technical, and organizational viewpoints.

Objective 4: To develop a conceptual framework for AI-based optimization of manufacturing processes, defining the main steps and challenges to be solved for successful implementation, from data collection to continuous monitoring of performance.

Objective 5: To investigate the future directions and wider implications of AI in manufacturing, with emphasis on its contribution to Industry 5.0 principles, sustainability, and competitive advantage for startups.

3. Research Methodology

This section presents the systematic methodology and research design for the study of manufacturing process optimization in startups by artificial intelligence (AI). It details the methodological framework, indicating the type of research, data collection strategies, and analytical techniques employed to achieve the study's objectives. This section will clarify the criteria for the selection of secondary sources and the role of advanced tools in the synthesis of literature, thus establishing the methodological rigor and scientific foundation of the study.

3.1. Research Design

This sub-section describes the research approach, research type and basic nature of data collection adopted to formulate the methodological framework for the exploration of AI in manufacturing optimization. This study follows a qualitative descriptive research approach with a wide literature review. This method choice is especially appropriate for an in-depth study of a fast changing and complex area like AI in manufacturing (Amaugo, 2025). Qualitative elements allow for the integration of different perspectives, identification of nuanced themes, and deep understanding of complex phenomena, such as the subtleties of human-machine collaboration or the qualitative impacts of AI integration (George, 2024). This description aims to give a complete picture of the current state-of-the-art AI applications, established frameworks, common challenges and emerging trends in optimizing manufacturing processes. It illustrates "*what is*" in this domain, based on existing knowledge (Aspers and Corte, 2019). The research also features an exploratory aspect, exploring nascent applications, novel conceptual frameworks and identified research gaps where the body of knowledge is less consolidated. The study does not test causal relationships through empirical experimentation but is a critical synthesis of existing literature to provide explanatory insights about the relationships between AI adoption and manufacturing performance outcomes. In essence, this is a secondary research study, based entirely on a thorough examination of pre-existing, publicly accessible data. The data sources used in this study are an enormous accumulation of academic journals, conference papers, industry reports, white papers and specialized books.

3.2 Method for Data Collection

The fundamental knowledge base was built by using a wide variety of reliable secondary data sources in this study. The study of academic journals and conference papers provided the scientific community with its research results, theoretical developments, empirical results and detailed methodology insights (LePine and King, 2010).

An important part of the data are key publications from engineering, computer science and management journals and proceedings of leading AI and manufacturing conferences. The peer-reviewed views are on AI methods, applications and their significance to various industrial settings. Industry reports and white papers published by consulting firms, market research organizations and technology companies (e.g., PwC, McKinsey and Gartner) provided valuable market trends, business insights, practical implementation experiences and strategic outlooks on the adoption of AI in manufacturing startups. They provided real world examples of economic impact and detailed analyses of challenges and opportunities for a specific industry. Specialized books on AI, smart manufacturing, industrial automation, and operational optimization provided foundational knowledge, established frameworks and deep dives into complex topics. Online databases and repositories offered in-depth information on current research, technological progress, and the collaborative ecosystems driving AI in industry. The secondary data have been gathered systematically in this study by the following three steps:

Step 1- Identification of Relevant Sources: A broad initial search was undertaken in academic databases and reputable industry sources using keywords such as "*AI in manufacturing*," "*manufacturing optimization*," "*Industry 4.0*," "*predictive maintenance AI*," "*smart factory*," and "*robotics AI*."

Step 2- Obtaining the Material: The relevant documents, mainly in PDF format (journal articles, conference papers, book chapters, white papers and reports) were obtained through academic subscriptions, open-access repositories, and direct downloads. This provided us with a complete library.

Step 3- Election and Filtering: Initially, each document obtained was checked for its direct relevance, academic credibility and recency. To make sure that the study is based on current insights, priority was given to peer-reviewed publications, reports by recognized industry authorities, and content published mainly in the last decade.

4. Data Analysis

This section outlines the basic analytical techniques used in the interpretation of the considerable amount of secondary data collected for this study. It details the use of content, comparative and thematic analysis to synthesize a holistic understanding of artificial intelligence (AI) in manufacturing startups. It assesses the impact of AI on the key performance metrics and the time-cost trade-off and, thereby, substantiates the scientific and analytical basis of the research.

4.1 Content Analysis

Content analysis is a systematic research method for analysing the content of textual, visual, or other types of communication data, converting qualitative data into quantitative insights (Parry, 2020). The main purpose is to detect patterns, themes, meanings and underlying messages within a dataset, so researchers can infer about the subject matter (Riffe *et al.*, 2023). Taking this large amount of secondary literature on the research of AI in manufacturing optimization into account, content analysis is a basic technique in this study to derive meaningful knowledge and make a synthesis of various points of view. In this research work, content analysis was adopted to conduct a systematic review and interpretation of the comprehensive collection, including academic journals, conference papers, industry reports, and specialized books. The aim was to summarize the large amount of textual data into structured insights that would inform the construction of a logical story addressing the research questions and objectives. The process was a series of iterative steps:

Step 1- Data Selection: The first step was to select highly relevant academic journals, conference papers, industry reports and specialized books. These were selected based on pre-defined inclusion criteria to ensure their relevance to AI in manufacturing optimization as described in Section 3. These documents together constitute the data corpus to be analysed.

Step 2- Coding and Categorization: An implicit systematic coding scheme was applied following the full research outline. We extracted and categorized key information, concepts, definitions, theoretical frameworks, specific AI applications, prevailing challenges, identified enablers and observed benefits. The process involved extracting key arguments, methods, results and case study information from each paper.

Step 3- Theme Identification: Through repeated analysis and cross-analysis of the entire dataset, recurrent patterns, dominant themes, and global concepts were identified. This enabled similar insights from different sources to be collected under a common thematic umbrella, such as particular AI techniques (e.g. machine learning, deep learning, reinforcement learning), specific application areas (e.g. predictive maintenance, quality control), ethical considerations (e.g. transparency, data privacy), and implementation models (e.g. edge-cloud continuum).

Step 4- Synthesis and interpretation: The data were then synthesized with the categories and themes. It was about bringing together information from various sources, establishing links, looking for supporting evidence or opposing viewpoints, and interpreting the information to create meaningful and insightful content for each study section. The goal was not only to summarize but also to offer a critical and analytical view of the state of AI in manufacturing optimization in startups.

The strategic deployment of AI in conducting content analysis greatly increased the efficiency and scope of this study. This enables a more thorough exploration of the enormous body of knowledge, which reduces the risk of human bias in the first-pass data interpretation and ensures a systematic approach to synthesizing complex information, thus enhancing the robustness and depth of the research findings.

4.2 Comparative Study

Comparative analysis is a systematic research method that consists of comparing two or more things to determine similarities, differences, and connections between them (Ragin, 2007). Its implementation allows researchers to uncover novel insights, compare relative strengths and weaknesses, identify patterns of convergence or divergence and ultimately arrive at more robust and nuanced conclusions (Bolbakov *et al.*, 2020). Comparative analysis is an important method used in this study to analyse various dimensions of AI in manufacturing optimization. It is more than description; it is an assessment and comparison of various approaches and their implications. The steps involved in the comparative analysis were:

Step 1- Comparative elements and criteria identification: For each comparison area, the specific entities were identified (e.g. two algorithms, two types of sensors, two industrial case studies). Matching criteria for comparison were set such as accuracy, latency, power consumption, cost implications, data requirements, scalability and applicability domain suitability.

Step 2- Systematic data extraction: For each comparative element, relevant data points, descriptive characteristics, reported performance metrics, and contextual information were extracted systematically.

Step 3- Conduct comparative analysis: The extracted data were then critically analysed to identify common features, unique attributes, observed trade-offs and performance differences between the compared entities. This required synthesizing information that may be presented disparately across sources.

Step 4- Drawing insights and conclusions: Insights were drawn based on the detailed comparisons, with respect to the relative strengths, weaknesses, and optimal use cases of the different AI techniques, applications, or frameworks. This informed best practices and strategic decisions on the implementation of AI in manufacturing startups.

4.3 Thematic Analysis

Thematic analysis is a flexible and powerful qualitative research method for identifying, analysing and reporting patterns or '*themes*' within a dataset (Christou, 2022). Its implementation goes beyond the description of content, trying to find deeper meanings, big ideas, and continuing concepts that appear across sources (Ahmed *et al.*, 2025). In this study on AI in manufacturing optimization, thematic analysis was a key step to consolidate insights from diverse document sources and to achieve a high-level understanding of the main focus areas, challenges, and future direction of the field. The main aim of the thematic analysis was to identify and describe the main and recurrent themes and important trends discussed by different authors (Christou, 2022) regarding the implementation and effect of AI in manufacturing. This strategy allowed to manage the huge and mixed

information in a structured way, allowing the synthesis of complicated details into the basic ideas which are defining the present panorama of the AI-driven industrial transformation. This was done in a few steps:

Step 1- Familiarization with data: This first step consisted of thorough engagement with the whole information source as described in Section 3. A detailed examination of each piece of information provided a good understanding of the content, the arguments and the context, and laid the groundwork for pattern recognition.

Step 2- Initial coding and pattern recognition: Relevant phrases, concepts, ideas, applications, benefits, challenges, and frameworks related to AI in manufacturing were extracted from the documents. At this step, the researchers were involved in a cyclical process of tagging and categorizing sections of text that appeared relevant to the research questions.

Step 3- Identifying themes: The first codes and patterns were then clustered into larger potential themes. This involved identifying similarities, connections and concepts that underpinned various individual points from different sources.

Step 4- Review and define themes: Potential themes were examined for distinctiveness, coherence and relevance to the overall research objectives. Themes were refined, merged, or dropped depending on their prominence and the extent to which they were supported by the data. Each theme was clearly defined and named to reflect the pattern it represented.

Step 5- Naming themes: The final themes were well explained with examples and evidence from the literature analysed. Thus, each theme was strongly supported by the empirical data.

Major Common Themes Identified

Through this systematic thematic analysis, a number of overarching themes appeared as central to the discourse on AI in manufacturing optimization:

Theme 1- AI as a Digital Transformation Enabler (Industry 4.0/5.0): A common theme is AI's fundamental role in enabling the wider digital transformation across manufacturing, often within the settings of Industry 4.0 and further into Industry 5.0. AI is viewed as critical to realizing smart manufacturing, cyberphysical systems, and highly connected factories that go beyond traditional automation to intelligent, flexible, and customized production. This transformation is particularly emphasizing the transition to human-centered approaches in Industry 5.0.

Theme 2: Holistic Optimisation Across the Value Chain: The literature consistently highlights that AI's impact is not confined to single processes but spans the entire manufacturing value chain, from early design and production to supply chain management and after-sales service. These include important applications such as predictive maintenance, smart quality control and inspection, dynamic production planning and scheduling, responsive supply chain and inventory optimization, and enhanced energy management.

Theme 3- Data Driven Decision Making (from Edge to Cloud): The proliferation of data generated by industrial internet of things (IIoT) devices, smart sensors and interconnected systems forms the bedrock of AI applications. A key and recurring theme is the architectural transition to distributed intelligence, using edge computing to process data closer to its origin, drastically reducing latency and bandwidth requirements, with the training of sophisticated AI models often taking place in the cloud or via meta-edge servers. It allows for real-time optimization and decision making.

Theme 4- Evolution of Human-AI Collaboration and Workforce Transformation: A prominent theme is the way AI is used to augment human capability, instead of replacing humans wholesale, which was an initial fear of massive job displacement. This trend calls for the creation of intuitive human-machine interfaces and the need for comprehensive workforce re-skilling and up-skilling programs to promote efficient human-machine collaboration within the factories of the future.

Theme 5- Challenges in Ongoing Implementation (Technical and Non-Technical): The literature shows a number of common problems in implementation despite obvious advantages. These include data quality and

availability issues, seamless integration with legacy systems, lack of skilled talent, huge initial investment costs, cybersecurity vulnerabilities, and the growing demand for explainable AI to build trust and ensure transparency. One concrete technical-regulatory gap is the certification of AI for safety-critical industrial systems.

Theme 6- Contribution to Sustainability in Production: This growing theme highlights the important part that AI plays in environmental and economic sustainability in manufacturing. This is done by optimizing energy consumption, reducing waste significantly (e.g. raw materials, defects, energy), improving resource utilization throughout the entire production lifecycle, and the possibility of more environmentally friendly production methods.

Thematic analysis thus served as a solid framework to organize the large literature review, providing a straightforward and holistic understanding of the major discourse areas, commonalities across different studies, and strategic implications of AI in the future of manufacturing optimization.

4. Proposed Reforms

This section acts as a transition from the theoretical framework of the literature review to a detailed and practical analysis of the implementation of artificial intelligence (AI) in optimizing manufacturing processes in startups. It covers the nuts and bolts of the big AI applications, providing a complete view of the entire workflow from data acquisition and pre-processing to model training and deployment. This section gives a tangible understanding of how AI-driven solutions are engineered to deliver tangible and measurable benefits on the factory floor, by detailing the specific AI technologies, architectures and methodologies used in areas such as predictive maintenance, quality control, production planning and robotics.

5.1 Manufacturing AI: Data Acquisition and Pre-Processing

Getting the data acquisition right and having strong pre-processing is the foundation for the successful implementation and optimization of AI in manufacturing. Data is the necessary fuel to AI models to learn, predict and make intelligent decisions that improve operations. Even the best AI algorithms cannot realize their full transformative potential without high quality, relevant and well-prepared data (Frank *et al.*, 2017). This subsection deals with the common types of manufacturing data, their main sources, and the key techniques used in data preprocessing.

5.1.1 Types of data in manufacturing

Modern manufacturing environments generate huge amounts of diverse data capturing almost every aspect of production:

1. **Sensor Data:** This involves real-time readings from a variety of physical sensors monitoring operational metrics. Examples of these are vibration signals, temperature, pressure, current, voltage, sound/noise, ultrasonic signals (for human detection or collision avoidance), light intensity, humidity, and even specialized environmental or material parameters, like soil moisture in agricultural manufacturing.
2. **Machine Logs and Operational Data:** These digital records are produced by equipment and include information on machine status, production parameters, process execution logs, and alarm events (Wolf and Lepratti, 2020). Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) systems provide data of a higher order related to operations and business.
3. **Quality Reports and Product Data:** This includes data related to product quality such as images of defects, results from automated or manual quality inspections, and detailed product specifications or Bill of Materials (BOM) data.
4. **Visual Data:** It includes 2D images, 3D point clouds from LiDAR sensors, and depth maps from different cameras and is used for object detection, quality inspection, and robot navigation.

5. External Data: More and more, data from outside the factory floor is being incorporated for a complete picture, including immediate market demand changes, weather forecasts, newsfeeds (for supply chain risk), and traffic data (for logistics optimization).

5.1.2. Infrastructure and Data Sources

The production and collection of this data rely heavily on a sophisticated infrastructure:

1. Industrial Internet of Things (IIoT) Devices and Smart Sensors: These are the first layer of data acquisition, and they are the front lines of data generation at the “micro-edge.” They are physical devices, often embedded directly into machines, to continuously measure and monitor in industrial environments.

2. Traditional Operational Technology / Information Technology Systems: Existing Operational Technology systems like SCADA and Information Technology systems like MES and ERP continue to function as important data repositories and interfaces, supplying historical data and context.

3. Robots and Automated Equipment: The current generation of robots and automated guided vehicles (AGVs) are more than actuators they are complex data producers, providing accurate operational data, vision streams and interaction records.

4. Communication Protocols: Different wired and wireless communication protocols are crucial for transmitting data from the edge to processing units. These include short-range technologies such as Wi-Fi and Bluetooth Low Energy (BLE) and long-range Low Power Wide Area Networks (LPWAN) such as LoRaWAN, as well as industrial protocols such as USART, SPI, and MQTT.

5.1.3. Data Pre-Processing Techniques

Raw data is usually in a format not directly useable by AI models. Pre-processing is a critical step in transforming raw data into a clean, consistent, and structured format suitable for analysis and model training.

Step 1: Cleaning the Data
This includes handling missing values, correcting inconsistencies and eliminating noise and irrelevant data points. For example, the Wiener filter is a filter technique to remove interference from sensor signals (e.g. vibration data).
Step 2: Data Transformation
The raw data is transformed into more easily processed forms by AI algorithms. For example, convert time-series data to frequency domain using Fast Fourier Transform (FFT) for vibration analysis, or convert images to grey scale or segmented mask for computer vision tasks.
Step 3: Feature Engineering
This is an important step, where we create relevant features from the raw data that show patterns and improve model performance. Examples of such are the extraction of micro-Doppler patterns from radar signals for gesture recognition or the derivation of morphological features (colour, size, shape, texture) from images of soybeans for quality assessment.
Step 4: Normalization and Scaling
It scales the data values to a common range or distribution (e.g. mean of zero and standard deviation of one). This is important to ensure that certain features do not unduly affect model training and to optimize the performance of algorithms.
Step 5: Data Augmentation
This technique is particularly critical in computer vision and time-series data, where synthetic variations of existing data (e.g., scale, time-shift images or bio-signals) are generated to artificially increase the size and

diversity of training data sets. This improves model generalization and robustness particularly when labelled data in the real world are limited.

Step 6: Data Quality Monitoring

There are methods that are used to constantly check and enhance the integrity, consistency and reliability of the gathered data. For instance, the Errors-to-Data Ratio (EDR) can be computed to spot duplicates, missing values or inconsistent observations.

Table 1: Data pre-processing steps

5.2 Detailed Analysis of Key AI Applications

AI is a game changer, opening new levels of optimization in the various functions of today’s manufacturing (Charalambous *et al.*, 2019). Putting aside theoretical potential, AI applications are now firmly embedded in industrial processes, delivering real gains in efficiency, quality, cost-effectiveness and adaptability. In this section, we provide detailed discussion on the main applications of AI which are revolutionizing manufacturing operations at their core, how they are implemented, what kind of AI technologies are used and the benefits they bring. Together these applications contribute towards making smart factories and Industry 4.0/5.0 principles a reality and demonstrate the power of AI to transform raw data into actionable intelligence and to automate complex decision making across the entire value chain.

5.2.1. Implementation of Predictive Maintenance

One of the most significant applications of AI in manufacturing is Predictive Maintenance (PdM) (Keleko *et al.*, 2022). It is a strategic paradigm shift from the traditional reactive (repair after failure) and preventive (time-based) maintenance models to a proactive, condition-based approach (Ucar *et al.*, 2024). AI-based PdM’s main objective is to foresee equipment failures before they occur, so that maintenance activities can be carried out exactly at the right time, maximizing operational performance, minimizing unplanned downtimes and drastically decreasing maintenance costs (Keleko *et al.*, 2022). The implementation of a comprehensive AI-driven PdM system requires a systematic multi-stage process that integrates advanced sensing, data analytics and intelligent deployment strategies. The various steps are as follows:

1) Data Collection and Acquisition (Sensors and IIoT):

- **Multi-Sensor Data:** PdM depends on the continuous acquisition of real-time, diverse data from equipment. The main parameters are vibration, sound/noise, temperature (thermography), current and voltage. For example, vibration accelerometers, microphones for sound, and clamp-on transformers for current. Advanced methods are also acoustic emission (AE) and radar signals for specific detections.
- **IIoT Infrastructure:** The main data producers are smart IIoT devices and smart sensors, usually installed at the “micro-edge”. These devices have embedded connectivity (e.g. Wi-Fi, LoRaWAN, Bluetooth Low Energy (BLE) and MQTT) to transmit data to higher edge levels or to cloud platforms.
- **Data Fusion:** The fusion of data from multiple sensor modalities (e.g., vibration and acoustic emission) increases the overall fault detection sensitivity and improves the resilience of the system to single sensor failures. This process combines data from multiple sensors, providing a more reliable and holistic view of the state of the equipment.

2) Data Pre-processing and Feature Engineering:

- **Data Preprocessing and Transformation:** Raw sensor data is often noisy and inconsistent. It requires important cleaning (e.g., noise reduction with Wiener filter) and transformation techniques. For time-series vibration signals, the Fast Fourier Transform (FFT) is frequently used to transform the data to the frequency domain, where fault-specific patterns are often more visible.
- **Feature Extraction:** Extract features of interest (e.g. RMS, kurtosis, peak-to-peak amplitude for vibration; micro-Doppler patterns for radar; morphological features for images) from the raw or transformed data. These features indicate certain characteristics that are indicative of equipment health or impending failure. We also use data augmentation (e.g., scaling, time-shifting) to increase the amount of training data and improve the generalization of the model.

- Normalisation/Scaling: Normalising/scaling features to a consistent range is done to stop features with bigger values from dominating the training process.

3) AI Model Training and Selection:

- Algorithm Selection: Different AI algorithms are used depending on the type of data and the prediction task. The machine learning (ML) algorithms employed are artificial neural networks (ANNs), decision trees (DT), support vector machines (SVM) and k-nearest neighbours (k-NN). For complicated pattern recognition, deep learning (DL) architectures are preferred.

- Model Training: Models are trained on large datasets of historical data from healthy equipment, different types of fault conditions and associated maintenance records. This supervised or unsupervised training process allows the models to learn the "normal" operational profile and identify deviations that are indicative of impending failure.

4) Model Validation and Evaluation:

- Metrics: The performance is evaluated using sensitivity (true positive rate), specificity (true negative rate), and balanced accuracy, which is particularly relevant for unbalanced datasets (where fault instances are rare). ROC curves are also used to evaluate the performance of classifiers at different thresholds.

- Testing for Robustness: Validation involves testing models on unobserved data, including scenarios that mimic real-world variability such as reinstalled equipment setups, to assess robustness beyond controlled lab conditions.

5) Deployment (Edge vs Cloud):

- Edge Deployment: Trained AI models are increasingly deployed directly on edge devices (e.g. microcontrollers such as STM32, FPGAs, specialized AI accelerators such as the Google Coral USB accelerator and industrial PCs) close to the data source. This strategy is crucial to enable ultra-low latency inference, reduce bandwidth cost, improve data privacy, and ensure reliability even with intermittent cloud connectivity.

- Cloud/Meta-Edge Processing: More complex model training, large-scale data storage, and aggregated analytics are generally done in the cloud or on powerful on-premises meta-edge servers. The hierarchical approach provides a compromise between local real-time responsiveness and large analytical power.

6) Monitoring, Alerting and Feedback Loop:

- Real-time Monitoring: AI models are deployed to continuously monitor equipment parameters, identifying anomalous behaviour or deviations from a learned healthy profile as they happen.

- Alerting: If anomalies are detected or when thresholds are predicted to be crossed, the system automatically sends alerts (e.g. dashboards, notifications) to the right people so that they can act in a timely manner.

- Continuous Learning: Data feedback on ongoing operations and post-maintenance is fed back into the system. This allows the model to be improved on an ongoing basis so that the AI models stay current, can adapt to changing conditions (for example, aging equipment or new ways of operating) and can get better at predicting over time. This results in a self-optimizing PdM ecosystem.

5.2.2 AI for Quality Assurance and Defect Detection

Quality assurance and defect detection are key functions in manufacturing and directly impact the reliability of products, customer satisfaction and profitability of the operation (Mittal and Gupta, 2021). To meet demanding quality requirements and produce flawless products on a regular basis, robust inspection processes are needed. Traditional quality control has relied on manual visual inspection subject to human fatigue, subjectivity, and inconsistency, or on inflexible, rule-based automated systems that lack the flexibility to detect subtle or new defects and struggle to scale for high-volume or highly customized production (Singh *et al.*, 2025). AI can provide transformative capabilities to overcome these limitations, enabling highly accurate, reliable and scalable quality assurance and defect detection using computer vision and statistical process control.

Automated Visual Inspection with Computer Vision:

Computer Vision (CV) using Deep Learning (DL) architectures, such as Convolutional Neural Networks (CNNs), has revolutionized visual inspection in manufacturing. CV systems allow machines to "see," interpret and analyse visual data from production lines with human or even superhuman precision, automating tasks that were formerly laborious and subjective. Visual inspection based on AI captures high-resolution images or video streams of

products and components using different types of cameras (such as 2D, 3D, industrial, infrared, global shutter, and multi-image sensors). These images are then passed to AI models, mainly CNNs, trained to process visual data. The process typically involves:

- **Defect Detection and Classification:** CNNs excel at automatically detecting and classifying various types of defects (e.g., scratches, foreign particles, misalignments, cosmetic flaws, and structural imperfections) on surfaces such as semiconductor wafers, electronic components, or finished products. They learn complex patterns from large datasets of images, which enables robust defect recognition even for subtle anomalies.
- **Image Segmentation and Object Recognition:** Using techniques like Mask R-CNN or UNet, AI models can identify specific regions of interest or individual objects in an image through pixel-level segmentation. This is important for applications such as accurately identifying and removing individual parts on an assembly line, or separating desirable raw materials from undesirable elements in food processing.
- **Data Acquisition and Pre-processing for CV:** The quality of the images is very important. Data preprocessing would comprise such steps as image normalization, conversion to grayscale or creating segmentation masks. Data augmentation (e.g. scaling, rotating, time-shifting images) is commonly used to increase the size of the dataset and improve model generalization for training.

Statistical Process Control (SPC) using Augmented AI

Traditional SPC applies statistical tools to monitor and control a process for it to operate at its best. AI improves SPC significantly by providing more advanced anomaly detection capabilities beyond traditional control charts and rule-based systems. AI algorithms can learn complex, multi-dimensional “normal” operational patterns from large amounts of data. They can then detect subtle deviations or “unknown anomalies” that may not be detected by fixed control limits or by human observation. This allows you to be more proactive in spotting potential process or equipment problems and turns SPC into a predictive quality management tool.

5.2.3 AI in Production Planning, Scheduling, and Control

Manufacturing requires production planning, scheduling and control to be efficient and profitable (Mittal and Gupta, 2021). They concentrate on deciding what to produce, when to produce it and how to allocate resources for maximum throughput and minimum cost. Traditional static planning systems with periodic adjustment cycles are no longer sufficient in the face of challenges such as mass customization, volatile demand, and disruptions. AI provides real-time adaptability, predictive insights and intelligence, allowing manufacturers to achieve higher efficiency.

AI to Improve Production Schedules

AI algorithms offer advanced tools to go beyond fixed schedules to create flexible production plans that adapt to real-time conditions in the manufacturing environment.

- **Dynamic Scheduling:** AI handles the massive complexity of real-time data from shop floors, supply chains, and market demands to produce adaptive schedules. This means constantly changing production sequences, setting priorities and managing the limitations of resources as events like machine breakdowns, lack of materials or sudden changes in the urgency of orders occur.
- **Multi-objective Optimization:** One of the strengths of AI for scheduling is that it can handle multi-objective optimization problems. Manufacturers are often faced with conflicting objectives such as reducing production time vs cost, energy consumption, or carbon emissions. AI algorithms can simultaneously find optimal schedules that balance these objectives, moving beyond traditional trade-offs to achieve synergistic improvements.

AI for Resource Allocation Optimization

The efficient allocation of manufacturing resources such as machinery, labour, materials and energy is paramount for maximizing efficiency and throughput. AI offers flexible capabilities for this important function.

- **Dynamic Allocation and Bottleneck Identification:** AI systems are constantly monitoring the real-time status and availability of all resources on the factory floor. By analysing live data, they can rapidly identify underutilized assets or bottlenecks that are appearing (e.g. a certain machine or work station becoming a constraint) and dynamically reallocate tasks or reroute production flows to ensure optimal throughput across the entire system.

- **Smart Equipment Selection:** AI models can help choose the best manufacturing equipment by considering various factors, such as its production capability, energy consumption, processing time, and goals for reducing carbon emissions. This ensures the equipment that is most efficient and sustainable is used for specific tasks, thereby reducing operating costs and increasing profits.
- **Inventory Management Integration:** While the field of supply chain optimization is separate, AI-based production planning directly impacts inventory levels. AI also helps with inventory costs by better predicting demand and improving production schedules, so that materials are available when needed and not too much of them.

AI for Production Control

Besides planning and scheduling, AI is crucial to the real-time control of manufacturing processes, enabling systems to operate autonomously and adaptively.

- **Real-Time Monitoring and Adaptive Control:** AI systems can monitor live data from production through connected sensors and IIoT devices. They can identify deviations from ideal process parameters, detect anomalies, and trigger automatic adjustments to keep the desired conditions constant, thus guaranteeing consistent quality and efficiency.
- **Control of Human-AI Teamwork:** AI helps human production planners and schedulers with predictions, best strategy proposals, and automatic routine adjustment management. This allows human operators to focus on complex problem solving, strategic decision making and handling unforeseen events that require human intuition.

5.2.4 AI for Supply Chain and Inventory Optimization

Modern manufacturing is only as good as the efficiency and resilience of the supply chain and inventory management (Manousiadou, 2024). The challenge of navigating complex global networks to ensure the timely availability of materials, minimize operating costs, meet fluctuating customer demand, and mitigate disruptions is becoming ever more important (Mishra *et al.*, 2024). The limitations of traditional static planning approaches and manual decision making are increasingly exposed in the face of more volatile conditions, with resulting inefficiencies, increased carrying costs and a vulnerability to unknown events (Manousiadou, 2024). AI delivers transformative capabilities to inject intelligence, responsiveness and resilience throughout the entire supply network, radically transforming how materials are managed and goods are moved. Some of the AI applications in supply chain and inventory optimization are as follows:

- 1) **Advanced machine learning (ML) models for demand forecasting:** The accurate demand prediction is the basis for an efficient supply chain and inventory optimization. AI can make demand forecasts much more precise and dynamic than simple historical averages, allowing it to identify complex, non-linear patterns. AI employs sophisticated ML models like neural networks and complex analytical tools to analyse large and diverse datasets. These datasets include historical sales data, real-time consumer behaviour patterns, seasonal variations, promotional effects and external macroeconomic factors. Additionally, relevant external events that could affect consumer demand, such as weather forecasts or news feeds, are incorporated. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTMs) are deep learning architectures that can capture the temporal dependencies, which makes them very effective in time series demand forecasting. AI can also power smart forecasting strategies, using sales data, consumer behaviour and seasonal information to predict the best ways to keep warehouses stocked. Better demand forecast accuracy reduces uncertainty throughout the supply chain leading to better production plans, correct inventory levels and better responsiveness to market shifts.
- 2) **Logistics Optimization and Routing:** AI has a major impact on the efficiency of logistical operations, such as transport, warehousing and distribution networks. It shifts from static route planning to dynamic, real-time optimization. AI uses real-time data on traffic conditions, vehicle availability, delivery constraints and even weather patterns to optimize routes, manage fleets and improve delivery schedules on the fly. Reinforcement Learning (RL) is increasingly being used for dynamic routing, teaching AI agents to find the best routes and re-routing strategies based on real-time events such as traffic congestion or road incidents. Optimization algorithms are also used to optimize warehouse layout, automate material handling and manage freight efficiently. These optimizations lead to significant reductions in transport costs, shorter delivery times, better utilization of logistics

resources (e.g. vehicle fleets, storage space) and higher delivery reliability, all of which have a direct impact on customer satisfaction.

3) **Inventory Level Optimization:** AI facilitates accurate inventory management, helping manufacturers find the right balance between the costs of holding inventory and the risks of stockouts. AI systems can combine smart forecasting with live inventory monitoring to dynamically determine optimal reorder points and safety stock levels. This helps to get rid of excess inventory with carrying costs, and to ensure there are enough materials to prevent production stoppages from shortages. Predictive analytics are used to analyse inventory data, supplier lead times, and forecasted demand to suggest ideal inventory replenishment strategies. It can even automatically maintain accurate inventory records to further optimize the operational efficiency. This results in drastic reductions in inventory carrying costs, better material availability, minimization of waste (e.g. obsolescence, spoilage) and better liquidity by freeing up capital locked into excess stock.

4) **Supply Chain Risk Prediction and Mitigation:** AI is an essential part of building resilient supply chains. With the ability to identify, predict, and mitigate potential disruptions before they develop into major problems, AI is a key tool in the supply chain. AI continuously monitors large external data streams such as news feeds, geopolitical analyses, weather forecasts and real time traffic data for early warning signs of potential disruption such as natural disasters, political instability, labour strikes or transportation network bottlenecks. Natural Language Processing (NLP) can be used to analyse unstructured text data (e.g. news articles, social media) for sentiment analysis or risk detection. Anomaly detection algorithms identify abnormal patterns in the supply chain data. Digital Twins of supply chain components can simulate the impact of disruptions and assess mitigation strategies. This type of proactive risk analysis allows manufacturers to prepare countermeasures, diversify suppliers or reroute logistics before a crisis fully develops, therefore improving overall supply chain resilience and reliability. It reduces the impact of unexpected disruptions to manufacturing and delivery.

AI integration turns traditional supply chains into agile, responsive and predictive networks. This holistic optimization results in lower operational costs, higher profitability, better customer satisfaction due to better order fulfilment and better transparency throughout the supply network.

5.2.5 AI for Energy Efficiency and Sustainability

Energy efficiency and environmental sustainability in manufacturing today are not merely operational issues; they have become critical strategic imperatives. With energy prices rising, environmental regulations tightening, and a global focus on reducing carbon footprints, industries are being pushed to become more resource efficient and environmentally responsible (Samuel, 2025). Existing static energy management and waste reduction approaches often lack the dynamic, precise and predictive capabilities required to optimize consumption in complex, real-time industrial environments (Karuna *et al.*, 2024). AI offers transformative solutions for increasing energy efficiency, cutting down waste, and advancing sustainable manufacturing across the value chain. Below are two common areas in manufacturing where AI can contribute towards energy efficiency and sustainability:

1) **AI for Smart Energy Management:** AI plays a key role in smart energy management in factories and for different production lines, moving from reactive consumption to active and real-time optimization. AI-driven predictive ML algorithms are employed to predict the energy demand based on extensive data including historical consumption, current production schedules, equipment status, and external factors such as weather that impact renewable energy sources. Being proactive means that energy planning can be done accurately and efficiently. AI combines precise demand forecasts with real-time energy availability to optimize the mix of renewable (solar, wind) and fossil-based sources, maximizing clean energy use while ensuring a stable, cost-effective supply for production. In addition, AI-based demand response systems help to reduce the electricity cost for industries by exploiting the time-variable tariffs. AI systems monitor energy use in equipment and plant zones in real time, identifying inefficiencies or anomalies and allowing for automated or guided adjustments, such as optimizing motor speeds, controlling HVAC, or tuning processes to minimize energy use without sacrificing quality or output. Forecasting and energy management tools also assist managers in addressing issues before they become problems, avoiding costly down time from energy waste.

2) **AI for waste reduction and resource optimization:** Apart from direct energy use, AI can also contribute to broader sustainability goals by enhancing resource efficiency and minimizing waste in production processes. AI analytics combined with real-time IIoT monitoring expose inefficiencies and anomalies in production that

result in waste. This allows for accurate quality checks on a cycle-by-cycle basis and avoids large material losses. For instance, in food processing, AI vision systems can be used to classify raw materials and water and energy consumption can be adjusted in real time to remove contaminants and optimize resource use. The use of AI can reduce the environmental impact across the entire life cycle of a product by optimizing resource flows, pollution and the carbon footprint of manufacturing operations. AI solutions can analyse production processes to find areas for environmental improvement and predict potential environmental risks.

5.2.6 AI in Robotics and Automation

AI has turned robotics and automation into smart, flexible, and collaborative systems that have long added precision and speed to manufacturing. Recent advances in AI are allowing robots to move beyond rigid programming to perform complex tasks more flexibly, autonomously and safely in factory environments.

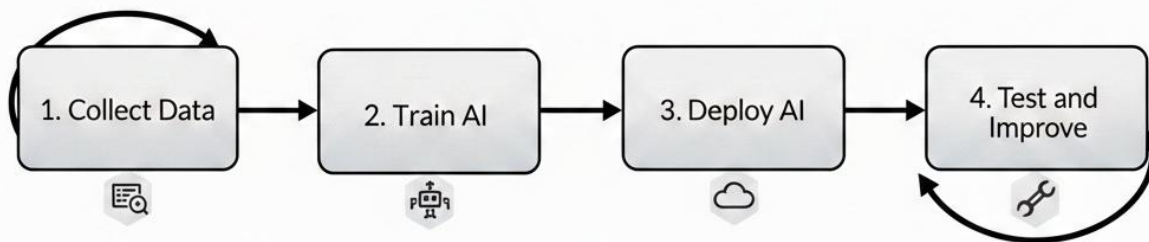


Figure 1: Adapted from *Artificial Intelligence for Digitising Industry Applications* by O. Vermesan et al., 2022, River Publishers.

Implementation Process: Data collection Training Deployment and Testing

The implementation of an AI-driven robotic system in manufacturing is a multi-stage process that concentrates on the integration of advanced sensing, intelligent data processing, and optimized deployment.

1) Data collection and pre-processing: The heart of an intelligent robotic system is to collect and comprehend data from its environment. The process heavily depends on multiple sensors and a strong preprocessing pipeline. A robotic system uses a number of sensors to perceive its environment. Robotic systems are increasingly using synthetic data to reduce the cost and time of manual data labelling. Vision-guided robots use open-source tools such as Blender to generate photorealistic datasets, depth images and object annotations to increase model robustness. In parallel, raw sensor data (e.g. ultrasound, radar) are pre-processed, noise filtered, features extracted (e.g. micro-Doppler pattern), normalized before training.

2) AI Model Training and Selection: An AI model is chosen and trained for the specific robotic task.

- Reinforcement Learning (RL): DRL is used for complex tasks where the optimal path is not known a priori. An RL agent learns optimal policies through interaction with a simulated environment, getting rewarded for actions that are successful, and improving its behaviour over time.

- Deep Learning (DL): Convolutional Neural Networks (CNNs) are the main architecture for computer vision tasks in robotics. These are trained on large annotated datasets (both real and synthetic) to perform object detection (e.g. YOLO) and instance segmentation (e.g. Mask R-CNN).

- Deployment-oriented training: AI models are usually trained with an optimization for deployment on resource-constrained devices. Other techniques such as quantization-aware training ensure that the model remains accurate even as its numerical precision is reduced to fit on an embedded microcontroller.

3) AI-Enhanced Robotic Task Execution: AI greatly augments the capabilities of robots, enabling them to carry out tasks that were once too complex or unstructured for traditional automation.

- Optimized Trajectories: AI algorithms, especially deep reinforcement learning (DRL), automatically optimize robot trajectories, minimizing the need for manual programming and enabling accurate, effective performance of tasks like welding or sealant application even in complicated, fast-changing settings.

- Smart Vision-Guided Systems: AI-powered computer vision allows robots to understand their environment, enabling them to pick out and work with randomly oriented or overlapping objects, a problem that

has been notoriously hard to automate. This improved perception allows robots to perform complex operations such as pick-and-place more flexibly and reliably.

- **Learning from experience:** Rather than being explicitly programmed, AI allows robots to acquire new skills from sampled experience. This enables them to adjust to changes in materials or processes, improving their performance through continuous learning over time.
- 4) **Deployment and Integration:** Once the AI model has been trained, it needs to be deployed on the robot's hardware and integrated into the larger manufacturing control system.
 - **Edge Deployment:** The AI model is deployed directly onto an edge device (such as an FPGA-based system-on-a-chip, an embedded microcontroller, or a dedicated AI accelerator, such as a TPU) for real-time applications, such as a robot's vision system or a safety system. This approach is key to ultra-low latency – a must for quick, real-time reaction to a dynamic environment.
 - **System Integration:** The AI is integrated using middleware and control architectures. Robot Operating System (ROS) is a popular choice because of its modularity and extensive library support. This allows the AI to send its outputs (coordinates of the detected object for example) and convert them into movement commands to the control unit of the robot. This creates a smooth sense-think-act loop.
 - **Human-in-the-Loop:** Even with advanced autonomy, human workers are still in the loop to make complex decisions and provide oversight. This allows the AI's outputs, such as the coordinates of a detected object, to be converted into movement commands for the robot's control unit, thus forming a seamless "sense-think-act" loop.

6. Future Implications

Based on the previous insights, in this section, we propose a phased framework for AI implementation that provides manufacturing startups with a practical roadmap to navigate the complexities, mitigate risks, and successfully integrating AI into their industrial systems. To successfully integrate AI into their operations and create smart, optimized processes, manufacturers need a systematic and structured approach. This framework provides a phased roadmap to guide new manufacturing startups through the complexities of AI adoption, covering everything from initial strategy to ongoing performance monitoring. It draws on industry initiatives, academic research, and real-world experiences, emphasizing a holistic perspective that encompasses both technology and organizational aspects.

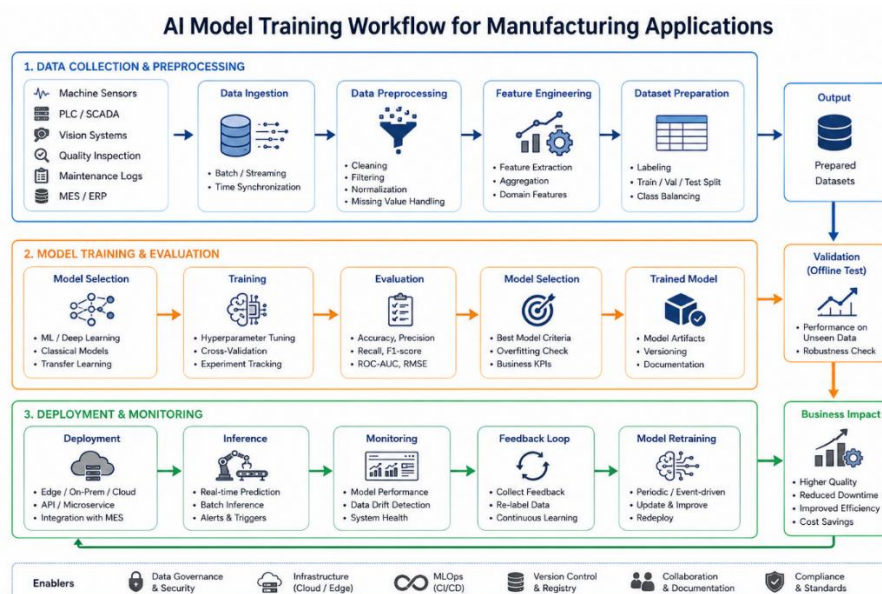


Figure 2: AI Model Training Workflow for Manufacturing Applications

PHASE 1: DATA COLLECTION AND PREPROCESSING

Data collection and preprocessing is a prerequisite for AI strategy. This phase is all about laying the groundwork to capture, transmit, and store the rich data that fuels AI models. But without a reliable and scalable data infrastructure, any AI initiatives will remain stuck in planning mode and never deliver real results.

1.1 Deploy IoT / IIoT Sensors and Devices: The first step is to install a network of smart sensors and industrial internet of things (IIoT) devices across the manufacturing environment. These devices are strategically placed on critical assets, production lines and environmental monitoring points to gather granular, real-time data on operations.

- **Types of Sensors:** Different types of sensors are used based on the specific data required for AI applications. These sensors include vibration and sound sensors to predict maintenance needs, temperature and current/voltage sensors to manage energy and check the asset's health, as well as vision systems (e.g. 2D/3D cameras from Basler, Zivid, or Intel) and LiDAR to inspect quality, identify objects, and help robots navigate. Where applicable, we also deploy a variety of specialized sensors such as human-robot interaction radar and environmental sensors.

- **Strategic Placement:** Sensors are strategically positioned to maximize data relevance and coverage. This involves concentrating on critical points that give insight into machine health, process parameters, product quality, and resource consumption. Many smart sensors are also capable of performing preliminary data filtering or processing at the "*micro-edge*," reducing the raw data that needs to be sent.

1.2 Data Acquisition Infrastructure: A strong infrastructure is established to allow the efficient and safe flow of data from its origin to the processing and storage layers.

- **Communication Protocols:** Reliable communication networks are required for data transfer from the shop floor. This requires a mix of industrial wired networks like Ethernet and Profibus and wireless protocols such as Wi-Fi for high bandwidth, LoRaWAN for long-range, low-power needs, Bluetooth Low Energy (BLE) for short-range communication and MQTT for lightweight messaging.

- **Edge Computing Layer:** Intermediate "*deep-edge*" devices (industrial PCs, gateways and embedded systems such as Nvidia Jetson Xavier AGX) are used to aggregate, filter, clean and pre-process data close to the source. This edge layer is important as it reduces latency, reduces bandwidth to cloud, improves data privacy and enables real-time local AI processing for critical applications.

- **Data aggregation and integration:** It is important to seamlessly integrate new IIoT data streams with existing operational technology systems (such as SCADA, Distributed Control Systems) and information technology systems (such as MES, ERP). This provides a consistent data pipeline to bring together disparate data sources for enterprise-wide AI analysis.

1.3 Data Storage and Management: Once data is acquired, it must be systematically stored and managed to ensure it is accessible and usable for AI model training and inferencing.

- **Data Lakes/Warehouses:** Scalable data storage is established. Data lakes generally hold raw, diverse data in its native format, whereas data warehouses are structured repositories for processed data suitable for analysis. These storage options are either cloud-based for scalability or on-premises for security and control.

- **Data Historians:** Special databases are used to store and retrieve time-series operational data efficiently over long periods. This is important for analysing trends in predictive maintenance.

- **Data Governance Policies:** Formal and robust data governance policies are developed to define clear rules for data ownership, access, quality, security and the entire data lifecycle. Good governance makes data trustworthy, compliant and handled with integrity. All are essential for reliable AI outcomes.

- **Automated Data Pipelines:** Automated Extract, Transform, Load (ETL) or Extract, Load, Transform (ELT) pipelines are developed for smooth, efficient, and standardized ingestion, transformation, and loading of data from acquisition points to storage systems.

PHASE 2: TRAINING AND VALIDATION OF THE AI MODEL

The core technical process of AI-enabled manufacturing optimization is training and evaluating AI models. It builds, trains and develops AI models that transform the clean data from Phase 1 into useful intelligence. This

stage needs to identify the right AI techniques for the particular manufacturing problems, and ensure the models are robust, accurate and optimized for the intended use cases.

2.1 Choose suitable AI techniques and algorithms: Selection of AI technique depends on the specific optimization objective and the type of data collected. A customized approach will be the most effective.

- **Problem-Algorithm Matching:** Classification problems (e.g., defect detection, anomaly detection) are matched with ML algorithms such as Support Vector Machines (SVM), Random Forests, or Artificial Neural Networks (ANNs). Regression models are well suited to predicting continuous values such as remaining useful life or energy consumption. Reinforcement learning is very powerful in dynamic control and decision making in complex scenarios. One can use genetic algorithms or swarm intelligence techniques such as Grey Wolf Optimizer, Beetle Antennae Search, etc. which are effective in solving complex optimization problems.
- **Deep Learning Architectures:** For visual data (e.g., quality inspection images, sensor spectrograms), we utilize Convolutional Neural Networks (CNNs) due to their excellent feature extraction abilities. When dealing with time-series data such as vibration signals or process parameters, Recurrent Neural Networks (RNNs) or Long Short-Term Memory networks (LSTMs) are used to learn patterns over time. Temporal Convolutional Networks (TCN) are another option for sequence data and provide a more stable training.
- **Complexity vs Deployment:** The choice of the model is also based on the trade-off between its complexity and the computing resources of the target environment; be it edge or cloud. More complex models typically require cloud or meta-edge computing for training, while simpler or optimized models can be done on micro-edge devices.

2.2 Data Preparation for Training: The high-quality data prepared in Phase 1 is now carefully organized for training the model.

- **Use Pre-processed Data:** The model training input is the clean, transformed and feature-engineered data from the previous phase.
- **Dataset Splitting:** Usually, the dataset is split into three parts: training set (to learn the model), validation set (to tune hyperparameters and perform early stopping to avoid overfitting), and a separate test set (to get a final unbiased estimate of the model's performance on unseen data).
- **Data Augmentation:** Data augmentation techniques are crucial for addressing the problem of data scarcity, especially for rare fault events or particular visual conditions. This includes the generation of artificial variations of existing data like scaling or rotating images, time-shifting bio-signals or the use of synthetic data generation tools like Blender to generate large, diverse and photorealistic datasets. This process helps the model to be robust and more generalizable.
- **Handling Imbalanced Data:** Techniques are used to reduce the effect of class imbalance (e.g., when "healthy" data is significantly more than "fault" data), so the model learns adequately from minority classes.

2.3 AI Model Training: The model training is an iterative process in which the AI algorithm learns from the data.

- **Iterative Optimization:** Process of feeding batches of training data into the model, calculating the difference between the model's output and the true labels (loss function), and modifying the model's internal parameters (weights and biases) using optimization algorithms (e.g., Stochastic Gradient Descent (SGD) with optimizers like AdaM) to reduce this loss.
- **Training Frameworks:** Popular open-source deep learning frameworks like TensorFlow (with Keras API) and PyTorch provide the essential tools and libraries to build and train complex AI models efficiently.
- **High-Performance Computing:** Constructing complex AI models, particularly those based on deep learning, usually requires substantial computational resources. Examples of high-performance computing resources adopted to speed up this process are graphics processing units and tensor processing units which enables faster development and training of larger and more complex models.
- **Continual Learning:** We can design models that continually learn in dynamic manufacturing environments by periodically retraining them with new data from ongoing operations. This approach helps keep

them current and enables them to adapt to changing conditions, such as aging equipment, new production methods or process variations.

2.4 Model Validation and Evaluation: The models are validated rigorously after training for their applicability to real-world scenarios.

- **Performance Metrics:** Metrics specific to the problem are used to measure the performance of a model. To evaluate the classification performance, we use metrics including accuracy, sensitivity, specificity, balanced accuracy, F1-score, confusion matrices and ROC curves. For the prediction we use metrics like mean absolute error (MAE) and root mean square error (RMSE).
- **Generalization and Overfitting:** The model should perform well on unseen data and not overfit (a model that performs well on training data but poorly on new data). Cross-validation techniques are used to ensure this. We use techniques like regularization, dropout layers and early stopping to fight overfitting.
- **Interpretability:** Early integration of Explainable AI (XAI) techniques aims to build trust and transparency in model decisions, especially for critical manufacturing processes where comprehension of AI reasoning is vital for human oversight and troubleshooting.

2.5 Model Optimization for Deployment: Models are often further optimized before deployment, especially on edge devices with limited resources. We can use TensorFlow Lite, Apache TVM, ONNX, STM32CubeAI etc., to apply quantization (lowering the number of bits in weights/activations), pruning (removing unimportant connections) and weight sharing. These methods significantly reduce model size, memory footprint and power consumption, enabling microcontroller deployment.

PHASE 3: DEPLOYMENT AND MONITORING

Deployment and monitoring is a critical phase in which trained AI models make the leap from a controlled environment to real-world manufacturing setup. The goal is to embed the AI into existing systems and processes such that the benefits are felt on the factory floor without interrupting production. During this phase we do the following steps:

3.1 Integrate AI Solutions with Existing Systems: The key component of this phase is the smooth interoperability between deployed AI solutions and the operational technology and information technology systems already available within an organization,

3.2 Deployment on Edge and Cloud: The strategy for deploying trained AI models determines where the intelligence resides and performs its inferences.

3.3 User Training and Adoption: A successful deployment is not only about technology, but also the people who will interact with AI systems.

3.4 Scaling of Pilot Project: When the AI initiative started as a pilot project, Phase 3 involves the careful scaling of the successful solution. This means to roll out its use step-by-step, from a small area such as a single machine, to an entire plant or the whole enterprise. As this expansion happens, scaling strategies need to take into account modularity, interoperability, and constant performance monitoring.

3.5 Cybersecurity During Deployment: The integration and deployment processes require robust cybersecurity measures, as connecting AI systems introduces new vulnerabilities to the industrial control network. Deploy robust security measures like encryption of data in transit and at rest, strict access controls, network segmentation, and regular vulnerability scans to safeguard AI models, sensitive industrial data, and communication channels from cyber threats.

3.6 Verification and Validation: The AI system undergoes a thorough verification and validation process before being put into full production. This includes thorough testing in the real world to verify that it works, is accurate and reliable, and meets all performance standards. This step confirms that the system works as it should, provides the expected benefits, and does not create any unplanned issues.

3.7 Building a Long-term Optimization Culture: Monitoring, assessing and iterating are not just technical activities, but they are key to building a company culture of continual improvement. This creates an environment where AI is an agile, ever-changing resource rather than a static fix. It promotes a culture of learning from data, responding to change, and continuous improvement in manufacturing, which guarantees ongoing value.

7. Conclusion

This research study on the optimization of manufacturing processes in startups using artificial intelligence (AI) has fulfilled all the set research objectives. Through a comprehensive and systematic review of existing literature, detailed analysis of AI applications, thorough examination of implementation challenges and enablers, and illustrative insights from global case studies, the overall goal of this study have been achieved. The research objectives have been achieved which include analysing the evolution of manufacturing optimization, exploring the various AI techniques and their applicability, identifying the benefits and challenges, proposing an implementation framework and assessing the future trends. A vast body of knowledge has been synthesized in order to achieve the objectives. In turn, the guiding research questions on how AI enhances efficiency and effectiveness, the challenges and enablers of AI adoption, its economic and operational benefits, and the suggested implementation framework have been addressed by presenting synthesized findings, and strategic insights.

The results of this study on AI in manufacturing optimization have important practical implications for managers, leaders and decision makers in the startup companies. AI is not simply a technical upgrade but a strategic imperative that requires a fundamental rethinking of operational models, resource allocation and organizational culture. To harness AI effectively, startups need proactive leadership and a holistic approach that combines technological progress with business goals and human resources development. Manufacturing startups need to develop a clear vision and a well-formed plan to adopt AI. This approach should tie AI efforts explicitly to concrete business challenges and broader organizational objectives, aligning tech to strategy instead of deploying it in a vacuum. Funding for AI infrastructure, talent acquisition and research and development should be adequate from the beginning. Entrepreneurs need to be visible champions of AI initiatives, visibly demonstrating their commitment and driving cross-functional buy-in to overcome internal resistance and facilitate organization-wide change. They should select pilot projects carefully, with a high likelihood of clear measurable success and a demonstrable return on investment, in order to mitigate risks and deliver early value. These pilots offer invaluable learning experiences, build internal expertise and are worthy of further investment before large-scale deployment in the organization.

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