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A Review Study on the Machine Learning Approaches to Manufacturing

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ABSTRACT

Manufacturing companies need constant development to remain competitive, which calls for adaptable workplaces and staff members that value lifelong learning. They also profit from systems for processing information and materials that are flexible and progressive. Machine learning has grown in popularity across a variety of industries, including entertainment, business, and industrial applications. It is a type of artificial intelligence that focuses on autonomous knowledge acquisition. Due to its adaptability and accessibility, new avenues for innovation have emerged, notably in the manufacturing sector. Machine learning techniques are becoming increasingly popular as the manufacturing sector moves towards Smart Manufacturing and Industrie 4.0. This study examines a decade's worth of manufacturing papers to assess how much machine learning is being used in that sector.

Keywords: *Machine Learning, Manufacturing, Technology, Industry.*

1.0 Introduction

The rapid advancement of CAD/CAM technology, notably in prosthetic and restorative dentistry, has had a significant impact on the discipline of dentistry. Dental education has improved in terms of cost, time, and predictability with the integration of these systems with biomaterials like high-strength zirconium oxide ceramics.

To incorporate the advantages of CAD/CAM technology into dental care, three primary procedures have been developed: digital impressions, digital models, and virtual articulators and face bows. The ability to generate a broad range of restorations for The enormous differences in acquisition techniques, CAD design mechanisms, and CAM production processes can make it difficult to develop specialized prosthetic solutions.a broad variety of restorations for unique prosthetic solutions might be difficult to build because of the wide variation in acquisition methods, CAD design tools, and CAM production techniques.

Machine learning (ML) has witnessed an increase in use in manufacturing over the past 20 years, with two surges in the 1980s and present utilization. Even though machine learning (ML) received a lot of attention in the 1980s, there was little industry adoption as a result of the challenges associated with using the methodologies with the available technology. In recent studies, cross-domain models for tying together information throughout the product life cycle have received less attention than domain-specific models.

However, as technologies like the Industrial Internet of Things, Industrie 4.0, and smart manufacturing are more widely used, more data is being produced, necessitating the use of automated ways to gather, transmit, evaluate, and take appropriate action on the data. Dynamically generating knowledge bases and figuring out minimum information requirements require ML tools that can analyse data, apply context, and build knowledge, especially earlier in a product's life cycle. This can lower the negative consequences of choices and raise the cost-effectiveness and standard of production programmes.

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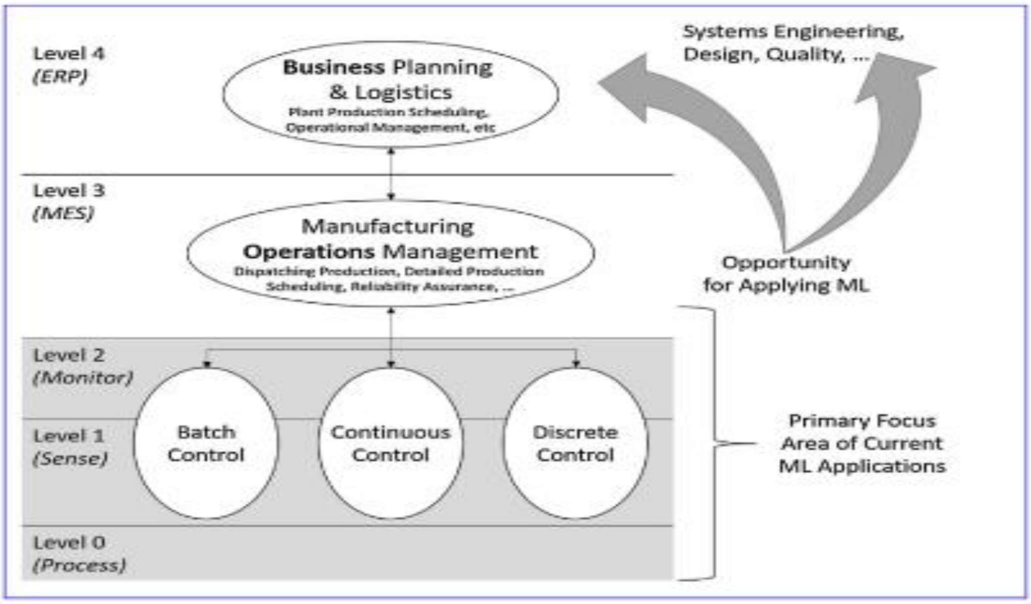
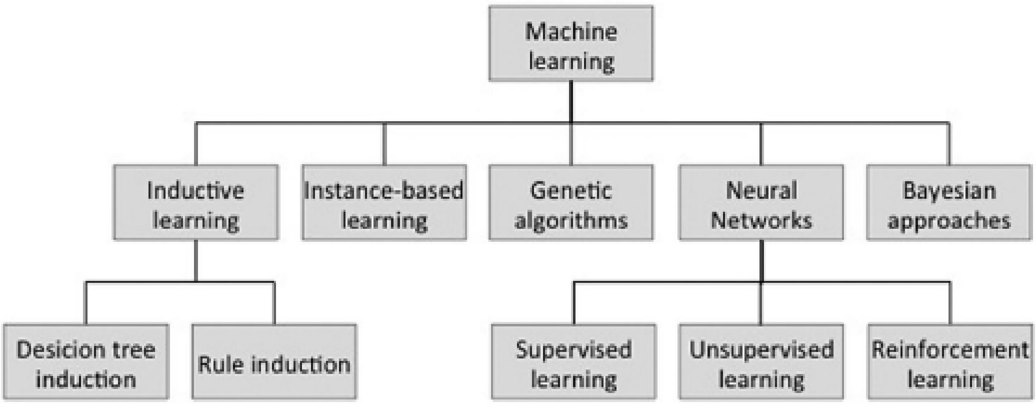




The paper seeks to make the case for why machine learning is a valuable tool for addressing current and future challenges in manufacturing, from a production perspective. It introduces relevant terminology and provides an overview of the different areas of machine learning, proposing a comprehensive structure.

The paper also discusses the advantages and drawbacks of various methods for manufacturing applications, aiming to give readers a broad understanding of the topic.

2.0 Challenges of the Manufacturing Domain

The importance of the industrial sector cannot be emphasized, despite its long history. Despite the fact that the manufacturing sector's GDP contribution has decreased in several industrialised economies over the past few decades, initiatives to revive it have been taken recently.

For instance, the European Union started the "Factories of the Future" program, and the US announced "Executive Actions to Strengthen Advanced Manufacturing in America." The manufacturing challenges of today are different from those of the past, and various international studies have outlined the main issues. These include the adoption of advanced manufacturing technologies, the increasing significance of high-value product manufacturing, the use of advanced knowledge, information management, and AI systems, the use of sustainable manufacturing processes and products, agile and flexible enterprise capabilities and supply chains, and innovation in goods, services, and procedures.

2.1 Advantages of machine learning application in manufacturing

In industrial systems, machine learning (ML) approaches have a number of benefits.

Their capacity to handle high-dimensional, multivariate data and extract implicit relationships from huge, complicated datasets, especially in chaotic circumstances, is one of their main advantages. In engineering and industry, where challenges are frequently data-rich yet knowledge-scarce, this is especially helpful. In some NP-hard manufacturing challenges, ML can reduce cycle time and scrap while increasing domain expertise and resource utilization,while reducing cycle time and scrap in certain NP-hard manufacturing problems.

Different ML techniques have varying advantages, but the ability to cope with high dimensionality is generally considered a positive feature. Additionally, user-friendly programs like Rapidminer make it easy to apply ML algorithms and adjust parameters for improved classification performance. Another significant advantage is ML's capacity to uncover implicit knowledge and relationships in data that was previously unknown.

ML algorithms can learn and adapt to dynamic, uncertain, and complex manufacturing systems, making them a powerful tool for continuous quality improvement. Their ability to quickly adapt to changing environments is often faster than traditional methods. While specific ML algorithms may have unique requirements for data availability and other factors, the overall effectiveness of ML in manufacturing has been successfully demonstrated

3.0 Applications in Manufacturing

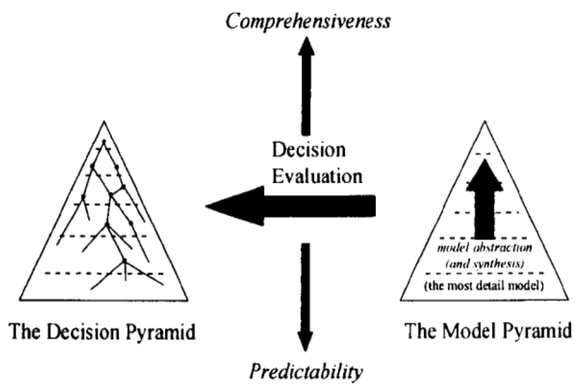
In the following sections, grouped by topics, a roster of applications of ML in manufacturing is presented. For each topic, a general introduction is followed by a description of major research projects as offered by our contributors and reported in major periodicals and selected conference materials.

3.1 Design

Several researchers have applied machine learning techniques to diverse design issues. Beginning with a specific problem situation where a fixed design model is assumed, the talk moves on to a method that combines model development with optimisation. Later, particular production system design issues are addressed. By filling in the design and manufacturing details of new, identical parts using data from current components, a design retrieval system, for instance, can reduce the amount of design work required.

In order to accomplish this, a set of completely defined, representative parts is used to anticipate the missing information on a new, partially defined part. Parts have been grouped using the COBWEB method based on an assessment of the likelihood that attribute values would be correctly predicted. A different suggested system retrieves design solutions through functional associations and can mutate the retrieved cases to further configurations. However, recognizing geometric invariance remains an unsolved issue. Finally, a four-layer ANN is suggested for the function specification step.

A Hierarchy of the Model Pyramid [128]



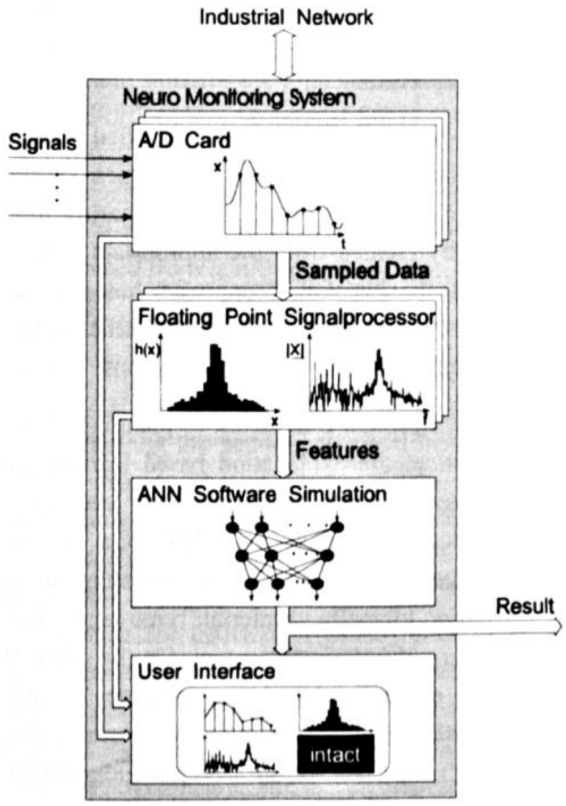
3.2 Process planning

Process planning has been highly successful in applying various learning methods, mainly due to the complexity of process planning expertise and the interrelated knowledge from multiple sources. Numerous applications have made use of easily accessible tools and methods, and research in this area has yielded useful outcomes outside of the technical community. The research in this discipline is categorised by application area in the following parts.

3.3 Process modeling, monitoring, and control

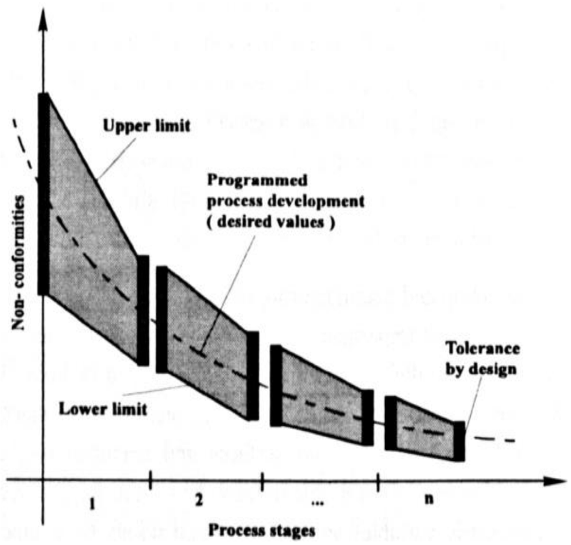
Several indications, including force, torque, temperature, mechanical vibration, and acoustic emission, which are the focus of various monitoring and control algorithms, can be used to evaluate manufacturing processes. It hasn't been possible to find a signal that works reliably under all circumstances and from all viewpoints, though. As a result, the incorporation of sensors has been acknowledged as a crucial step in this area, providing advantages including information redundancy. In the event of sensor failures or mistakes, this redundancy can reduce total uncertainty and improve system reliability.

Schematic of Neuro Monitoring and Diagnostic Systems



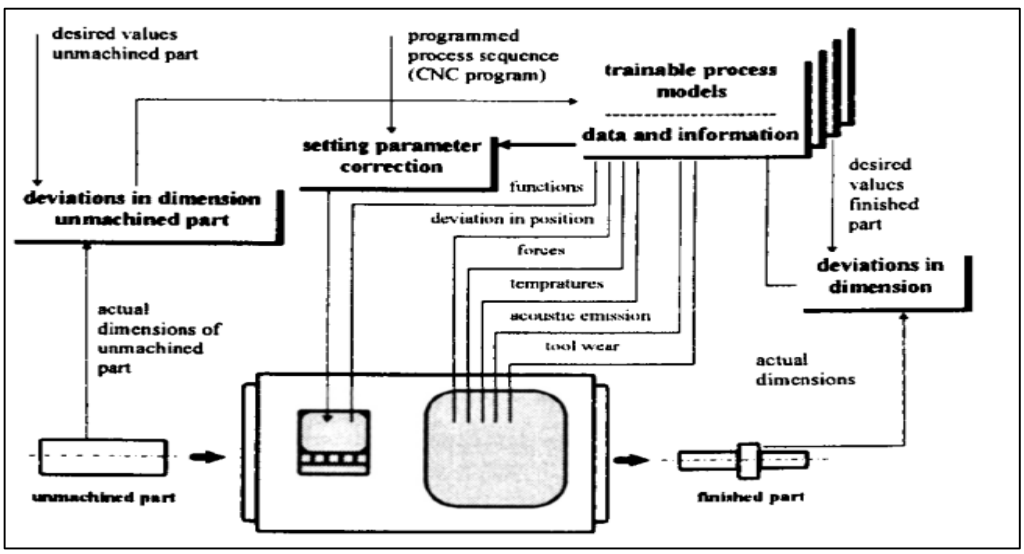
3.4 Automated inspection, diagnostics and quality control

Competition and the need to minimise costs on the one hand, and the rising demand for quality and dependability on the other, create conflicting demands for modern manufacturing. In order to achieve maximum efficiency, process parameters are frequently pushed to the limits of machine tools, yet high-quality standards can only be met under reasonable machining settings.

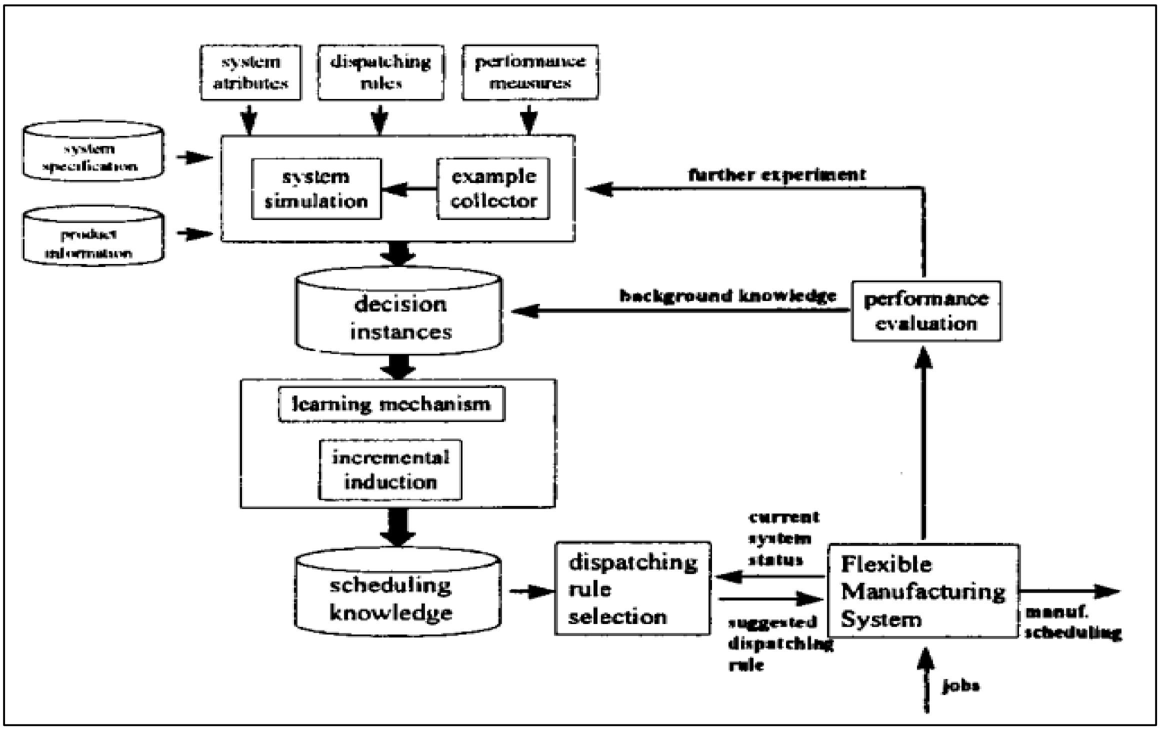


Complex quality control procedures are needed in highly automated, just-in-time manufacturing to guarantee error-free assembly of parts. Manufacturing requires the use of inspection, diagnosis, and quality control.

Quality Control Loop for Zero-defect Manufacturing [242]



Architecture of the Learning-based Dynamic Scheduling System



High accuracy measurements of deviations in dimensions, form, and position are made using coordinate measuring machines (CMMs). For sporadic process measurements, interchangeable measuring heads are utilised. These heads can be connected to controllers so that any necessary adjustments can be made.

3.5 Production planning and control

It was acknowledged in 1990 that scheduling lacked expert and heuristic knowledge since there weren't enough human experts who could be validated. This issue has been addressed by a system that uses the production system's history database to make suitable scheduling decisions in a dynamic context. The system combines goal-directed conceptual clustering, case- and rule-based methods, and simulation to provide synergistic effects. Another study modified system performance by combining weighted heuristic priority rules with an induction module. The name of this simulation system is KBSim. In another study, the performance of a "artificial memory" system and a traditional heuristic algorithm were evaluated in order to handle the scheduling problem of knowledge organisation. The outcomes demonstrated that the former performed only a little bit better.

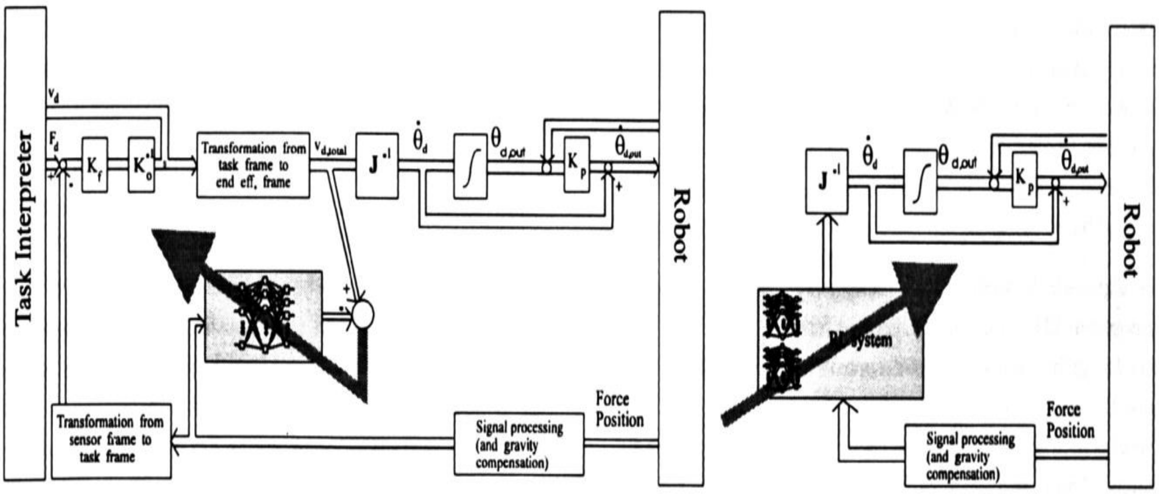
3.6 Robotics and assembly

Machine learning can be used to improve a variety of learning tasks found in robotics and assembly. During the development and deployment of robots, machine learning can support a variety of tasks, including initial knowledge acquisition, programme generation (i.e., robot programming and world-model acquisition), and action and world knowledge refinement. (i.e., acquiring new knowledge to solve new tasks, refining existing knowledge, and correcting it to help the robot adapt to uncertain and changing environments).

4.0 Conclusion

1. In today's industry, efficient management and manufacturing are crucial for progress and improvement. An effective system is needed to help industries overcome challenges.
2. Computers have been an essential tool in many fields, including manufacturing, aerospace, and healthcare. Integrations that synchronize data and provide better results have become increasingly important. CAD/CAM (Computer-Aided Design and Computer-Aided Manufacturing) is a popular integration that has brought significant efficiencies to the industry.

Learning Control Architecture: Supervised Training in the KA phase (left) and RL Phase (right) [172]



3. CAD is used to create designs on modern computers, which are then simulated and manufactured.
4. CAD applications can be combined with artificial intelligence and machine learning to optimize designs and make the system more advanced and creative.
5. CAM is similar to CAD, but it manages manufacturing tasks and resources, including materials and personnel, to find the best solution.
6. Adding AI and machine learning to CAM can improve system performance and efficiency. CAD/CAM integration streamlines the design and manufacturing process by providing a single system application for all operations and data flow.
7. CAD/CAM integration has also improved computer graphics systems, making it easier to perform automated drawings and engineering analyses such as stress-strain.

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