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Machine learning-supported manufacturing: a review and directions for future research

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ABSTRACT
The evolution of manufacturing systems toward Industry 4.0 and 5.0 paradigms has pushed the diffusion of Machine Learning (ML) in this field. As the number of articles using ML to support manufacturing functions is expanding tremendously, the main objective of this review article is to provide a comprehensive and updated overview of these applications. 114 journal articles have been collected, analysed, and classified in terms of supervision approaches, function, ML algorithm, data inputs and outputs, and application domain. The findings show the fragmentation of the field and that most of the ML-based systems address limited objectives. Some inputs and outputs of the analysed support tools are shared across the reviewed contributions, and their possible combinations have been outlined. The advantages, limitations, and research opportunities of ML support in manufacturing are discussed. The paper outlines that the excessive specialization of the reviewed applications could be overcome by increasing the diffusion of transfer learning in the manufacturing domain.

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Machine learning; manufacturing functions; state-of-the-art; artificial intelligence; process selection; quality control

1. Introduction and background

The transformation of manufacturing towards being smart, digital, and autonomous has accelerated. Key issues in this transformation process are flexibility, readjustment, and resilience of manufacturing systems as expressed by (Kusiak, 2017) with the concept of smart manufacturing. Computer control, information technologies, production management software, and sensor networks are prerequisites for a manufacturing company to move into that direction. However, these devices and systems are not sufficient for a manufacturing system to be considered smart unless its overall function is controlled by intelligent technology (Mittal et al., 2016) favouring stability and repeatability of the manufacturing process.

The rapid growth of fast, accurate, and adaptive Artificial Intelligence (AI) applications tends to reduce tasks performed and controlled by humans (Chanal et al., 2021). Within AI, Machine Learning (ML) has made inroads in the manufacturing industry,

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where the maturity of the integration of ML systems is witnessed by their capabilities of dealing with complex issues, e.g. time-dependent dynamics (Long et al., 2023; Yang et al., 2022). The key success factor for the introduction of ML in the manufacturing domain is likely its ability to model and predict complex connections between experimental and simulation data. ML applications in the manufacturing industry appear to be a valuable option because of the requirement for increased autonomy of manufacturing systems. Moreover, the massive integration of sensors is leading to the production of a large amount of data by the manufacturing industry. This availability of raw data creates an opportunity to use intelligent systems in this area to solve various categories of problems.

This paper attempts to highlight its capabilities with a focus on the mechanical engineering aspects of manufacturing.

1.1. Fundamentals of machine learning

ML is traditionally divided into five categories based on the nature of the training approach used: supervised learning (SL) (Hoefer & Frank, 2018), unsupervised learning (UL) (Papananias et al., 2020), reinforcement learning (RL) (Yu et al., 2020), semi-SL (Dogan & Birant, 2021; Paturi & Cheruku, 2021), and self-supervised learning (SSL) (Kahng & Kim, 2021). In SL, the targeted outputs are defined alongside the inputs, whereas the output is not specified in UL. Regression and classification are the two subcategories of SL and are used in interpreting continuous or categorical input data, respectively (Kang et al., 2020). Clustering and association algorithms are categorized under UL. The clustering algorithm groups the data according to similarity while the association algorithm is based on rules to find important relations among variables in a database (Srinivasan et al., 2020). RL is about the acquisition of the optimal behaviour in an environment to choose the best solution for pursuing a given goal (Kononenko & Kukar, 2007). The combination of SL and UL algorithms results in semi-SL. Unlike SL, a large amount of unlabelled data is used in semi-SL (Reinders et al., 2019). SSL methods can process datasets consisting entirely of unlabelled data. In a first stage, labels are generated automatically in SSL approaches. In the residual of the paper, the meaning and characteristics of ML categories, standard algorithms and statistical functions are taken for granted. In this regard, the authors used the definitions and descriptions available in Kononenko and Kukar (2007), which can be considered a guide for understanding ML algorithms.

1.2. Machine learning in the manufacturing industry

The increased popularity of ML in manufacturing has led to the publication of review articles aimed at summarizing, classifying, and suggesting future applications. Bertolini et al. (2021) classified ML support in manufacturing into four areas, namely: maintenance management, quality management, production planning and control, and supply chain management. Current trends in ML and manufacturing were given alongside the number of most cited articles and the most cited authors. In another review, Dogan and Birant (2021) categorized articles according to learning algorithms and manufacturing functions: scheduling, monitoring, quality, and failure. An alternative ML classification in manufacturing was proposed by Sharp et al. (2018) based on decision support, data management, plant and operations health management, and lifecycle management. Furthermore, the use of support vector machines (SVMs) and neural networks (NNs) had become more popular as presented in Sharp et al. (2018), due to their capability to work with large-dimension datasets and their practical effectiveness. Paturi and Cheruku (2021) presented and compared the performance of each ML algorithm used in the manufacturing industry. Manufacturing functions were also considered here. Kang et al. (2020) focused on production line applications of ML algorithms, rather than manufacturing in general. ML algorithms were classified based on industry domains. The article also claimed that ML was applied in the metal manufacturing and semiconductor industry since these processes are complex and a large amount of data is created by production lines. Moreover, ML algorithms and manufacturing applications were investigated according to their suitability, advantages, challenges, and applications (Wuest et al., 2016). Nassehi et al. (2022) focused on the application of AI in manufacturing within scheduling, monitoring, quality assessment, and failure detection. The articles were grouped according to AI applications such as genetic algorithms (GA), SL, UL, and RL. The importance, challenges, opportunities, and future developments of AI were discussed too. Mozaffar et al. (2022) presented manufacturing data and databases. Moreover, the scholars emphasized the importance of AI in manufacturing for design, process control, and monitoring. This review (Mozaffar et al., 2022) pointed out several future research directions including data-driven modelling discovery, data-driven design methods, data-driven control and monitoring, and database security in the manufacturing field. Fahle et al. (2020) included articles between 2015 and 2020 in their review with a focus on the factory environment. The main classification categories were manufacturing process planning and control, predictive maintenance, quality control, in situ process control and optimization, logistics, robotics, assistance, and learning systems. Those scholars indicated that NN and decision tree (DT) algorithms were the most widely used ML algorithms in the mentioned period. Those approaches are flexible and can adapt to a variety of problems, which makes them appealing for industrialists. Qi et al. (2019) reviewed articles that include ML support for additive manufacturing (AM). The main classification was on design for AM, monitoring, and process-property-performance relations. Moreover, the details of artificial neural network (ANN) algorithms were given alongside challenges and potential solutions. Likewise, reviews focused on the use of ML for AM are (Meng et al., 2020; C. Wang et al., 2020).

In Figure 1, the aforementioned review articles are summarized based on the terms used to classify ML support in manufacturing. The vertical axis indicates the number of articles included in each review. The horizontal axis shows the classification methodology followed by the review articles, which has overall included five categories, namely: performance, supervision, functions, input and output, and domain. In detail, performance indicates the success rate of the ML algorithm implemented in each reviewed article. Inputs and outputs are the data that are processed by the ML algorithm and what is provided as a result, respectively. Domains refer to specific industries and manufacturing processes considered in reviewed articles. Functions are the manufacturing activities and operations overall ascribable to manufacturing and production. In this paper, the reviewed articles are classified considering those manufacturing functions typically

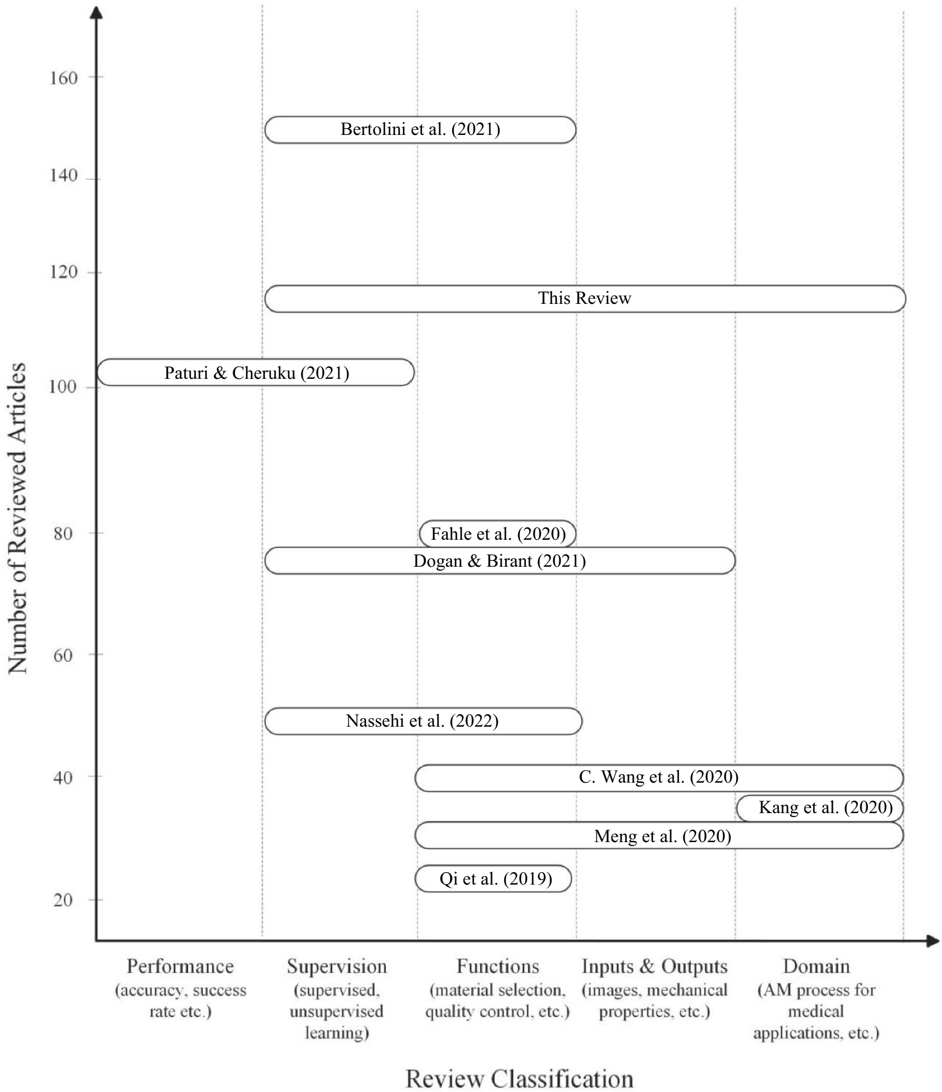

Figure 1. Classification of review articles.

managed by mechanical engineers, namely: material selection and property prediction, production scheduling and planning, manufacturing process selection, production monitoring, and quality control operations (details below).

It is worth noting that a large variety of classifications and viewpoints are presented in these reviews. This provides indirect evidence of the wide spectrum of applications of ML in manufacturing but also of the academic interest in this area. Although almost all reviews paid attention to manufacturing functions, the considered ones are uneven across these articles. Few review articles included management, lifecycle assessment (Sharp et al., 2018), and supply chain management (Bertolini et al., 2021), while others focused on the physical or mechanical dimensions of industrial manufacturing applications only (Dogan & Birant, 2021; Meng et al., 2020; Nassehi et al., 2022; Qi et al., 2019). Conversely, Kang et al. (2020) focused on an application domains or manufacturing functions only.

1.3. Objectives and need for an updated review

The objective of the present paper is to update the state-of-the-art of ML applications in the manufacturing industry alongside their categorization according to established criteria, so that reviewed contributions can be compared across multiple aspects. As the number of contributions in the field is skyrocketing, three restriction criteria were deliberately introduced to make the number of analysed papers manageable.

- Journal articles only were reviewed and analysed, which are typically considered the most reliable and rigorous.
- The present paper limits its outreach to functions ascribable to the mechanical and engineering dimensions of the manufacturing process in line with some of the analysed reviews (Dogan & Birant, 2021; Meng et al., 2020; Nassehi et al., 2022; Qi et al., 2019).
- Articles describing and testing specific applications were considered only.

As a result, beyond updating the state-of-the-art, the current review classifies ML support in manufacturing based on manufacturing functions, inputs and outputs, supervision, and application domains with more than 100 contributions analysed, as evident in Figure 1. Overall, all classification criteria found in previous reviews were considered with the only exception of performance evaluation. The performance evaluation of the applied ML algorithms is disregarded here for the following reasons:

- The performance evaluation was not reported in all the contributions included in this review.
- The performance of ML algorithms can be evaluated with different criteria and models, as well as the different context of use plays a fundamental role. Thus, reporting and comparing performance evaluations could be misleading for readers.
- In general, the transfer of performance from one context to another is a major challenge and makes the comparison of performances difficult.

As mentioned, a more comprehensive review of the ML support in manufacturing applications is needed also because the number of applications is increasing rapidly. As visible from Figure 1, although Bertolini et al. (2021) included the largest number of contributions, the focus was not only on manufacturing but also on other linked industrial applications, which made this review broader. Conversely, the aim here is to provide a comprehensive view on the ML support in manufacturing intended with a narrower meaning, namely those manufacturing functions ascribable to mechanical engineering. Five classes of functions (listed below) were chosen by considering and combining the functions broadly used in (Bertolini et al., 2021; Dogan & Birant, 2021).

- Material selection and property prediction: this function includes articles that use ML algorithms to predict a mechanical property or to select a material for a manufacturing process.
- Production scheduling and planning: articles pertaining to this function propose an ML algorithm to support the timing and sequence of manufacturing operations.
- Manufacturing process selection: this function includes ML algorithms to support decisions when a suitable manufacturing process has to be chosen out of a number of alternatives.
- Production monitoring: this function includes articles that implement ML algorithms during production with the scope of monitoring the fulfilment of manufacturing requirements and the continuity of the manufacturing process.
- Quality control operations: this function includes articles that apply ML algorithms for inspection and verification of design requirements after the manufacturing process is completed.

This review is organized as follows. The following section describes the methodology to search for and select pertinent articles. In the third section, the reviewed ML applications in manufacturing and the classification thereof are discussed; the main reasons and expected benefits behind the use of ML are stressed. Directly extractable information (trends of publication numbers, keywords, etc.) are also included in this section. In the fourth section, the outcomes of the current review are commented; possible links and similarities across the reviewed articles are highlighted. The fifth section reports the authors' view on the possible evolution of the field, the open issues to be approached, and the identified research opportunities. Finally, in the last section, the main findings are summarized and conclusions are drawn.

2. Research methodology

The current study was conducted in line with the objectives and approach of a 'mapping review/systematic review' based on the typology of reviews described by Grant and Booth (2009). Accordingly, the authors first collected contributions through a literature search using the Scopus database. The search was conducted in June 2022 by using search terms in the field 'Title, Abstract, and Keywords'. The search terms linked through an AND operator belonged to two distinct groups, as presented below.

(1) Words addressing the presence of ML in the article, thus alternative '* learning' terms connected through an OR operator. Here, * assumes adjectives associated with ML as in the definitions given above, e.g. machine, supervised.
(2) Words designating the field of manufacturing through the 'manufactur*' string.

By using Scopus functions, the results were subsequently filtered in terms of

- language: English
- source type: Journal
- subject area: engineering OR material science.

The Scopus search and subsequent filtering resulted in 3887 articles. The abstracts of these articles were first analysed to check if the concepts of learning and manufacturing were linked in the articles. This led to the initial selection of 155 articles. Then, the full texts of these articles (where available) were examined; the ones indicating in the introduction that they targeted the use of ML for supporting manufacturing were selected for inclusion in the current review. This work led to the identification of 95 articles. To increase the comprehensive nature of the review, 19 journal articles were added to the current review by applying the snowballing methodology and considering citations included in the reviews illustrated in Figure 1. Hence, 114 journal articles were eventually selected for the scope of the current review. The article selection methodology is summarized in Figure 2.

Before processing the retrieved documents, the sample of articles included in the current review was compared with some of the reviews presented in Figure 1; the most similar in terms of classification (Dogan & Birant, 2021), the review that contained the largest sample (Bertolini et al., 2021), and the most recent review (Nassehi et al., 2022). Based on these comparisons, the collected sample includes one hundred articles not considered in the reviews mentioned earlier, which fully justifies the need for an updated and original review.

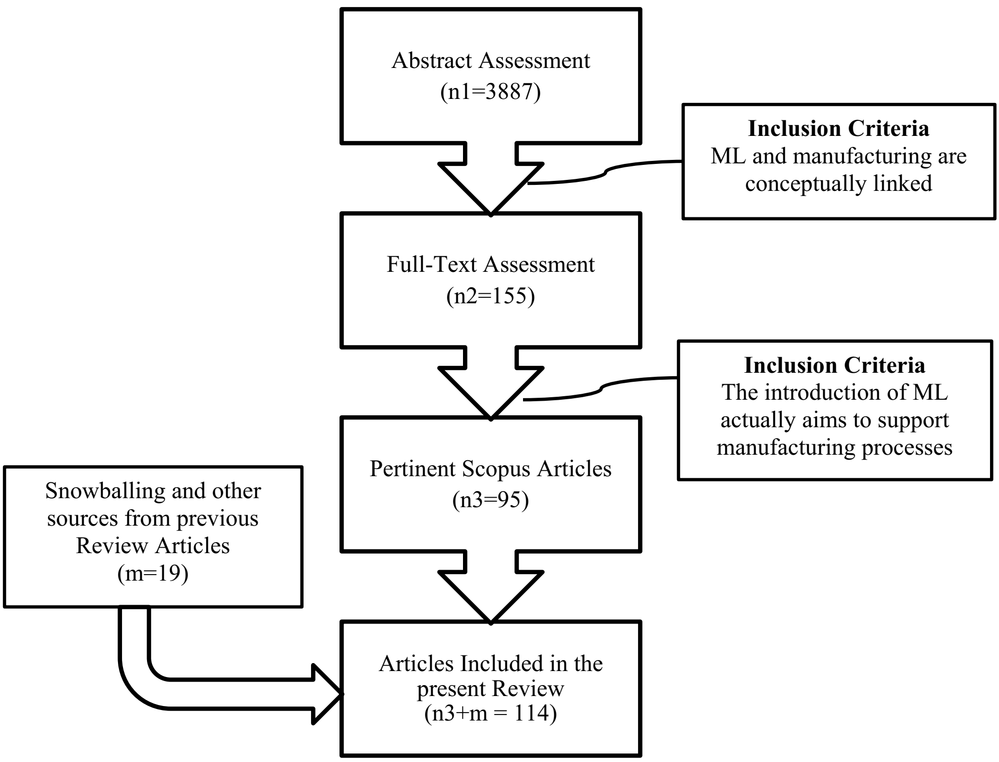

Figure 2. PRISMA diagram for showing the article selection process of relevant documents describing the support of ML in manufacturing.

Table 1. Classification of ML support in material selection and parameter prediction articles.

Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(C. C. Zhou et al., 2009)	Developing and optimizing the multi-objectives of material selection	ANN and GA	SL	Mechanical, environmental, and economic properties	An optimum solution as selected material	Multi-objective optimization for sustainable products
(Xiong et al., 2012)	Developing NN and regression-based algorithm for prediction of bead geometry in robotic gas metal arc welding for rapid manufacturing	ANN	SL	Welding speed, nozzle-to-plate distance, wire feed rate, arc voltage	Bed width and height	Robotic gas metal arc welding for metals
(Sood et al., 2012)	Investigation of understanding the effect of raster angle, layer thickness, raster width, part build orientation, and air gap on the compressive strength of a test specimen	ANN	SL	Raster angle, air gap, part orientation, layer thickness	Compressive strength	–
(Pilania et al., 2013)	Developing a quick and simple way to select materials with ML	KRR	SL	Polymeric chains	Atomization and formation energy, lattice parameter, electron affinity, electronic dielectric, spring, and total dielectric constants, bandgap	Polymer manufacturing
(R. Liu et al., 2015)	Decreasing passed time during the material selection	Search path refinement and search space reduction	SL	Youngs modulus, yield strength, magneto strictive strain, composite function, and weighted gaussian function	Youngs modulus, yield strength, magneto strictive strain, composite function, and WGF	HDMD for Galfenol manufacturing
(Strasser et al., 2018)	Developing an ML algorithm for selecting variables, building and evaluating models for adaptive parameter settings in manufacturing processes	ANN, Linear regression, cross-validation, square mean error	SL and UL	Dimension of each part in each step, the weight, temperature, pressure, and forces applied to the produced part	Quality measures	–
(Radetzky et al., 2019)	Determining manufacturing parameter properties for the grinding process	Agglomerative hierarchical clustering and DT (C4.5)	SL and UL	Grinding disc, cutting fluid, linear feed, volume flow of cutting fluid	Avg roughness, Avg surface roughness, and gloss value measured in gloss units	Grinding for cutlery manufacturing
Source	Objective	Algorithm Main Algorithm	Supervision	Inputs	Outputs	Application Domain

(*Continued*)

Table 1. (Continued).

Source	Objective	Algorithm: Main Algorithm	Algorithm: Supervision	Algorithm: Inputs	Algorithm: Outputs	Application Domain
(Lee & Tsai, 2019)	Improvement of yield issues in colour filter manufacturing and identifying important parameters that affect PS which is a part of a colour filter	Stepwise regression, DT, RF, partial least squares, backpropagation NN	SL	Process steps, tool parameters, recipes, and metrology measurements such as RGB colour layers, indium tin oxide layer, black matrix, and PS	PS thickness and 10 more parameters selected	Thin film transistor liquid crystal display components manufacturing
(Gjelaj et al., 2019)	Developing of turning process based on analysing tool path length, tool selection, and machining parameters for the turning process using AI	Multi-objective GA	SL	Feed rate, cutting speed, depth of cut	Cutting force, feed rate, cutting speed, depth of cut	Turning for metal manufacturing
(M. Zhang et al., 2019)	Predicting the high cycle fatigue life of laser powder bed fusion stainless steel 316L with the use of neuro-fuzzy based ML algorithm	ANFIS NN	SL	Layer thickness, layer power, tensile properties, scan speed, post-processing temperature	Fatigue life	LPBF for stainless steel manufacturing
(Srinivasan et al., 2020)	Developing a methodology to accelerate the searching of the AM processing space for suitable printing parameter sets	SVR	SL	Power, velocity, efficiency, and depth-to-width ratio	Efficiency and depth-to-width ratio	General LPBF process
(Kopper et al., 2020)	Predicting the ultimate tensile strength for high-pressure die-casting of aluminium	RF, SVM, DT, NN	SL and UL	Avg fast head and rod pressure, avg intermediate head and rod pressure, avg slow head and rod pressure, biscuit length, cavity fill time, die close tank level and temperature, and so on	UTS, tensile strain, and quality index	High-pressure die-casting for Aluminium manufacturing
(Wanigasekara et al., 2020)	Developing an ML-based predictive model to predict the manufacturing parameters of composites using automated fibre placement	ANN	SL	Lay up speed, hot gas torch temperature, consolidation source	Short-beam strength, interlaminar shear strength, and elastic modulus	Automated fibre replacement for unidirectional composite manufacturing
(Herriott & Spear, 2020)	Investigating the performance of data-driven modelling for material property prediction of a simulated microstructural dataset	Ridge regression, DT, and CNN	SL	Volume, axis lengths, aspect ratio, number of neighbours, equivalent spherical diameter, omega-3, Schmid factor, micromechanical Taylor factor, the average distance to the grain boundary	Yield strength	Metal AM for stainless steel 316L

(*Continued*)

Table 1. (Continued).

Source	Objective	Algorithm Main Algorithm	Supervision	Inputs	Outputs	Application Domain
(Chang et al., 2021)	Developing a parameter-selecting algorithm for magnetic material manufacturing with SLM	DT	SL	Oxygen concentration, laser power, scanning speed, and operating frequency	Iron loss and permeability	SLM for soft magnetic composites
(Torquato et al., 2021)	Developing a multi-objective methodology to optimize the electric arc furnace-based steel production and to reduce energy consumption and scrap cost	Non-dominated sorting GA II	SL	Individual scrap price, scrap availability, tap additives, and ambient temperature	Optimal scrap parameters for lower energy consumption and scrap cost	Electric arc furnace for steel manufacturing
Source	Objective	Algorithm Main Algorithm	Supervision	Inputs	Outputs	Application Domain
(H. S. Park et al., 2021)	Improving Ti-6Al-V4 SLM-fabricated part quality and selection of optimum process parameters	DNN	SL	Laser power, laser scanning speed, layer thickness, hatch distance	Density ratio and surface roughness	SLM for Biomedical applications
(Barrionuevo et al., 2021)	Predicting the relative density of 316L stainless steel 3D printed parts	SVM, DT, RF, gradient boosting, gaussian processes, kNN, ANN	SL	Laser power, scanning speed, layer thickness, hatch spacing, and particle size	Relative density	SLM for stainless steel manufacturing
(Moges et al., 2021)	Predicting the melt-pool width of laser powder bed fusion additive manufactured parts	Regression (Polynomial)	SL	Solid and liquid density, solidus and liquidus temperature, solid and liquid specific heat capacity, solid and liquid thermal conductivity, latent heat of fusion, dynamic viscosity, coefficient of thermal expansion, preheat temperature, laser spot radius	Melt-pool width	LPBF
(McGregor et al., 2022)	Predicting the part geometry and use of these predictions to qualify the parts	SVR and SVC	SL	CAD dimensions, x, y, r locations in build, hardware set, material, thermal cure, layout, feature category, and class	The predicted geometry of the parts	–
(Maitra et al., 2022)	Predicting the relative density of Ti-6Al-4V alloy manufactured by SLM	GPR and MLR	SL	Laser power, scanning speed, hatch spacing, layer thickness, volumetric energy density	Relative density of Ti-6Al-4V alloy	SLM for Ti-6Al-4V alloy manufacturing
(He et al., 2022)	Assisting textile manufacturing firms to optimize the overall process performance and product quality as a whole	DQN based RL and RF	RL and SL	Water content, temperature, pH, and treating time	Textile properties: colour depth, colour indexes for colour variation in three dimensions	Textile manufacturing

(*Continued*)

Table 1. (Continued).

Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(P. Wu et al., 2022)	Reducing manufacturing time, labour cost, and additional machining costs	DL and GA	SL	Material removal rate, energy consumption, surface roughness, and maximum cutting force	Feed rate, spindle rotation speed, depth of width, and depth of cut	Machining
(B. Wang et al., 2022)	Optimizing processing window for femtosecond laser-induced nanostructures	k-means clustering, PCA, ANN, RF, DT, SVM, kNN, NB classifier	SL and UL	Laser power, fluence, scanning speed, and scanning times	Optimized operation window for the best quality	Femtosecond laser-induced periodic surface structures manufacturing

3. Machine learning applications in manufacturing

The following subsections are articulated according to manufacturing functions indicated in the first section; the classification and analysis of the reviewed articles are given under each section (Tables 1,2,3,4 and 5), where they are further categorized based on:

- ML algorithm
- ML inputs
- ML outputs
- ML supervision
- Manufacturing application domain.

In Figure 3, the number of journal articles classified in the current research is presented based on the corresponding manufacturing functions and publication years. It is worth noting that article numbers increased after 2017 in a nearly monotonic way. The year 2017 can be thus interpreted as a turning point in terms of the diffusion of ML systems for the manufacturing industry. The trajectory of growth lets us believe that a further increase of published articles is to expected also in coming years.

In order to further analyse the selected article set, the VOSviewer tool was used to construct and visualize bibliometric networks. Figure 4 shows the co-occurrence of keywords and reflects the main themes mentioned in the selected article set. In Figure 4, the node size represents the number of articles that include the related keyword while the lines between the nodes correspond to the link among the keyword terms. The fact that largest nodes are related to algorithms, statistical functions, typologies of learning, rather than manufacturing operations suggests that computer science plays a key role. The authors interpret this as a technology-push situation. In other terms, this evidence suggests that, in most cases, ML scholars might have attempted the implementation of algorithms in manufacturing. Correspondingly, manufacturing scholars could

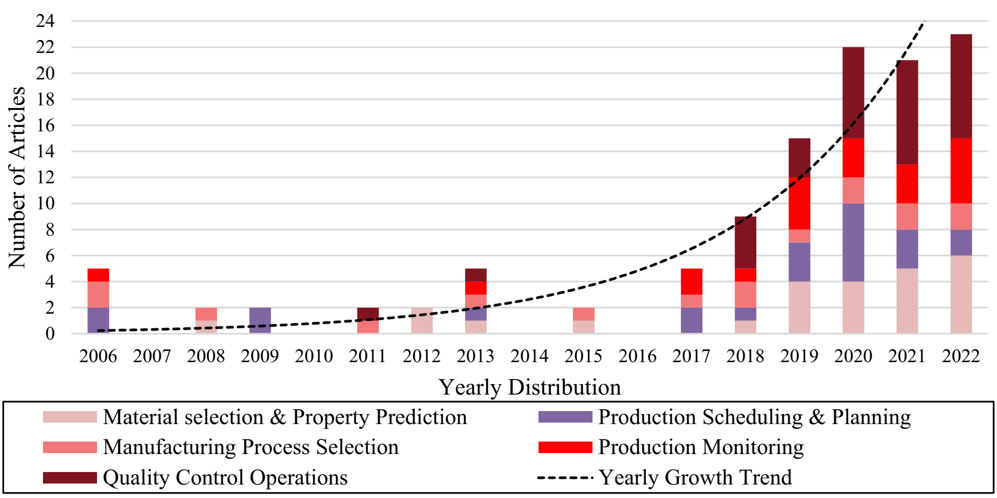

Figure 3. Number of articles included in the current review based on manufacturing functions and publication years.

Table 2. Classification of ML support in manufacturing scheduling articles.

Source	Objective	Algorithm: Main Algorithm	Algorithm: Supervision	Algorithm: Inputs	Algorithm: Outputs	Application Domain
(Mönch et al., 2006)	Modelling semiconductor wafer fabrication machines as parallel batch processors in the diffusion and oxidation areas	NN and DT	SL	Machines, job families, batch machine factor, batch processing machine capacity, tightness of due dates, ready time tightness, ready time range	Feasible schedule	Wafer fabrication for semiconductors
(Csáji et al., 2006)	Developing an adaptive iterative distributed scheduling reinforcement algorithm that works with a market-based production control system	RL	RL	Boltzmann formula modified with branches, machine status, makespan, unexpected events time	Job schedule status (either job cancellation or new job arrival)	–
(Shiue, 2009)	Developing a knowledge base class selection mechanism for supporting various product mix ratio environments	DT	SL	Number of jobs, mean utilization of machines, the standard deviation of machine utilization, mean utilization of load/unload stations, pallet buffers	Ranking of scheduling strategies	–
(Salehi & Tavakkoli-Moghaddam, 2009)	Optimizing initial sequences of process plan and selection of machine, cutting tool, and tool access direction	GA	SL	Geometrical information, tolerance, surface finish, tool information	Process plan	–
(Mehrjoo & Bashiri, 2013)	Developing a robust decision-support methodology based on PCA and LR for detailed production planning	PCA and LR	SL and UL	Machine properties, equipped gasses, daily plan, painted body stock, scheduled receipt, emergency sales demand, actual daily product	Scheduling support system	Production planning and control
(H. Li, 2017)	Decreasing the makespan and deadline of the flexible manufacturing systems	GA and RL	SL and RL	Encoding, gene length, crossover operator, mutation operator	Route planning	Flexible manufacturing system for automotive industry
(Shahrabi et al., 2017)	Enhancing the performance of dynamic job shop scheduling method	DQL	RL	Number of jobs on the shop floor, mean operations processing time	Optimum schedule	–
Source	Objective	Algorithm Main Algorithm	Supervision	Inputs	Outputs	Application Domain

(*Continued*)

Table 2. (Continued).

Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(Priore et al., 2018)	Developing a dynamic ensemble method to select the most appropriate dispatching rule over time with ML algorithms	DT, case based-reasoning, backpropagation NN, SVM	SL	Flow allowance factor, the mean number of alternative machines for an operation, utilization of each machine, mean number of parts in the system, mean utilization of FMS, the ratio of the utilization of the bottleneck machine to the mean utilization of the FMS	Mean tardiness and mean flow time of the proposed strategies	–
(Lin et al., 2019)	Developing a smart manufacturing factory framework that investigates job shop scheduling problems with edge computing	DQL	RL	Number of jobs, number of machines, features of customer orders, total processing time, average completion time, makespan, average queuing time	Optimized working schedule	Job shop scheduling for semiconductor manufacturing
(De Jong et al., 2019)	Proposed an algorithm to generalize the job shop scheduling for a quick and accurate makespan regression	CNN with TL	SL	Job distribution, job types, job priority, processing time, number of automatic guided vehicles (AGV), and AVG's speed	Makespan	–
(Tan et al., 2019)	Industrial robot assembly process for planning, scheduling, and modelling based on real-time data acquisition with edge computing, actuator network, and wireless sensors	QL	RL	Assembly configurations, task, processing time, setup time	Makespan	Industrial robot assembly scheduling
(Abidi et al., 2020)	Developing an intelligent scheduling algorithm for FMS using a hybrid ML algorithm	Fuzzy classifier and DBN	SL and RL	Buffer size, the arrival rate of parts, average speed, first come first served performance, shortest processing time performance, earliest due date performance	Scheduling rules: first come first serve, shortest processing time, earliest due date	–
(Gonzalez Rodriguez et al., 2020)	Developing an AI system to help the decision-making process in closed-loop supply chain manufacturing systems	RT and FIS	SL	Remaining production, differences between input and output, available time, classification rate	New classification rate and Externalizations	–
Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(Jiang et al., 2020)	Achieving the best connection between printing paths in different process parameters to have a better dimension accuracy	DNN	SL	Print speed, line distance, layer height, and filament extrusion speed	Print speed, line distance, layer height, and filament extrusion speed	FDM

(*Continued*)

Table 2. (Continued).

Source	Objective	Algorithm: Main Algorithm	Algorithm: Supervision	Algorithm: Inputs	Algorithm: Outputs	Application Domain
(T. Zhou et al., 2021)	Developing a new AI scheduler for data-driven dynamic scheduling of manufacturing jobs with uncertainty for smart factories	DRL	RL	Job type, initialization time, nominal operating time, target completion time, machine type, machining speed factor, energy efficiency factor, waiting time for remaining workloads, remaining buffer length	Job Schedule	Job scheduling for smart factories
(I. B. Park et al., 2020)	Minimizing the makespan of the multichip product scheduling by inspecting die attach and wire bonding stages of a semiconductor production line	QL	RL	Job types, waiting operation, alternative machines, initial setup status	Job Schedule	Semiconductor Production Scheduling
(Altenmüller et al., 2020)	Developing and application of self-learning and autonomous algorithm to address order dispatching with strict time constraints in job shops	QL	RL	Number of machine groups, number of machines per machine group, number of product types, size of buffers before machine groups, order release time interval, setup times, time-coupling constraints	Job shop layout	–
(Kim & Zohdi, 2022)	Generating an optimal tool path for the SLS process	CNN and DL	SL	Ambient and initial temperatures, convection coefficient, thermal conductivity, density, the specific heat capacity of PA12, laser radius, laser scanning speed, optimal extinction coefficient, and material grip gap size	Optimal tool path	–
Source	Objective	Algorithm Main Algorithm	Supervision	Inputs	Outputs	Application Domain
(W. Wu et al., 2021)	To increase the response speed of decision-making-based process planning	DRL	RL	Total number of cutting tools, the total number of machine tools, and the tool approaching directions	Production planning model	Process planning for dynamic machining
(X. Shao & Kim, 2021)	Proposed an effective scheduler based on self-SL to solve complex job shop scheduling problems	Self-supervised long short-term memory	SSL	Number of jobs, position order, order of procedure in the machine, the ratio of procedure to all machines, the ratio of processing time to sum, etc.	Makespan	–
(Oluyisola et al., 2022)	Proposed a methodology for production planning and control	DNN and LR	SL	Preliminary production plan	Updated plan model	–
(J. Li et al., 2022)	Proposing a digital twin model for flexible assembly systems	DRL	RL	Workpieces, assembly actuators, surroundings, physical restrictions	Digital factory schedule	Flexible assembly lines

have studied the implementation of ML as a possible means to solve well-identified problems in a fewer cases.

The subsections that follow are structured according to the analysed manufacturing functions. They concisely report the needs for introducing ML algorithms and the resulting advantages.

3.1. Material selection and property prediction

ML algorithms offer the opportunity to replace and improve traditional systems by predicting process parameters based on the state of the product and manufacturing conditions (Strasser et al., 2018). For example, the SLM technology requires human observation while selecting the most suitable properties and using magnetic materials during production. ML algorithms offer a great opportunity to optimise process parameters for SLM to reduce dimensionality (H. S. Park et al., 2021). For some operations (SLM process (Chang et al., 2021; Maitra et al., 2022) and textile manufacturing (He et al., 2022)), it is difficult to formulate a relationship between the inputs and outputs without availing of an autonomous system. ML algorithms were used to predict and optimise process parameters for SLM to improve mechanical properties of products (Barrionuevo et al., 2021). Hence, ML algorithms are suitable for these operations since they can handle a large amount of data, formulate a relationship among the inputs and outputs, eliminate human observation (Chang et al., 2021; He et al., 2022), reduce the high dimensionality of parameters used in a manufacturing operation (B. Wang et al., 2022), reduce the processing time (P. Wu et al., 2022), improve the accuracy of prediction (Moges et al., 2021), and reduce the cost of a manufacturing operation (B. Wang et al., 2022).

Overall, ML can thus be used in the material selection procedure for better, more accurate, and quick prediction models by using inputs based on mechanical properties, machine working conditions, and environmental conditions. Hence, it can make intelligent decisions from unclassified data while creating prediction models. The classification of the reviewed articles that include material selection and property prediction are presented in Table 1.

The articles listed in Table 1 are ordered according to the year they were published in. The list starts from the oldest and ends with the most recent article. The same ordering criteria are used for the other manufacturing functions (Tables 2,3,4 and 5).

3.2. Production scheduling and planning

ML applications have been widely adopted to operate complex scheduling systems in the manufacturing industry (W. Wu et al., 2021) and overcome typical limitations of traditional scheduling systems. One of these limitations is low efficiency and scheduling capacity (Serrano-Ruiz et al., 2022). Simulation-based scheduling systems are promising; however, they mostly use empirical rules and historical data, which reduces the accuracy of these systems (T. Zhou et al., 2021). Another limitation is the significant requirement of human knowledge to design a production schedule for assembly lines (J. Li et al., 2022). Moreover, a job shop scheduling system can be challenging and expensive while operating without the supervision of an advanced system for controlling and management, which may result in inefficiencies and delay production (X. Shao & Kim, 2021). ML

Table 3. Classification of ML support in manufacturing process selection articles.

Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(Ip & Regli, 2006)	To determine the best manufacturing process based on shape feature information	SVM	SL	3D CAD Models and surface curvature	Prismatic-machined or cast-then-machined	–
(Deb et al., 2006)	Evaluation of the applicability of the backpropagation NN method for determining all possible machining operations for rotationally symmetric components	ANN	SL	Feature type, dimensions, tolerance, surface finish	Feasible machining operation sequences	Machining for rotational parts
(Sener & Karsak, 2008)	Developing fuzzy regression and fuzzy multiple objective methodologies for advanced manufacturing process selection	Fuzzy regression	SL	Cost, throughput, routing flexibility, volume flexibility, improvement in downtime, work in progress	Selected alternative of manufacturing technology	FMS
(Rajput et al., 2011)	Proposed a time-dependent decision-making methodology that includes the current and future behaviour of alternatives with quantitative and qualitative criteria to finalize an optimal choice for the wafer fabrication process	Fuzzy analytic hierarchy process	SL	Normalized thickness mean, normalized thickness uniformity, engineer's experience, standard procedures, multi-response, on-line education	Rank of manufacturing alternatives	Wafer fabrication
(Evans et al., 2013)	Generating a distinct experience-based decision support system to calculate confidence factors for the successful adoption of potential technologies for a given set of requirements	Fuzzy DT	SL	Manufacturing decision problem requirements, crisp or fuzzy attribute, technology confidence factor, success rating of the project	Manufacturing technology suggestion	–
Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(Venkataraman et al., 2015)	Developing a methodology for manufacturing method selection based on ANN	ANN with Levenberg – Marquardt Algorithm	SL	Setup time, material type, material cost, cost of piece, capability, tool change, tool cost, manpower, wastage, production rate, quality status	The rank of the manufacturing processes to select the most suitable one	Planning, forming, shaving, shaping, hobbing, milling processes
(Mukherjee, 2017)	Developing an algorithm for sustainable process selection by ranking the sustainability indicators	k-means, SVM, and partial least squares	SL and UL	Sustainability footprint	Rank of sustainability indicators	Sustainable manufacturing
(Hoefer & Frank, 2018)	Generating a method for manufacturing process selection automatically during conceptual design	KNN, DT, and RF	SL	Three property metrics were used: geometry, machining, and orientation metrics	Machining process or casting then machining process	Casting and machining

(*Continued*)

Table 3. (Continued).

Source	Objective	Algorithm: Main Algorithm	Supervision	Inputs	Outputs	Application Domain
(Hamouche & Loukaides, 2018)	Automating and enhancing the sheet forming selection process	ANN	SL	Matrix representations of spinning, deep drawing, stretch forming, air bending, roll bending	Geometrical prediction of the given shape	Sheet forming
(Marini & Corney, 2019)	Process selection methodology to minimize the consumption of raw material and machining by following a near-net shape procedure	Fuzzy logic	SL	Cost, component geometry, production volume, material, tolerances, surface roughness, tool, equipment, mechanical properties	Rank of feasible processes	Casting, forging, and AM technologies
(Ghahramani et al., 2020)	Providing an advanced solution for controlling manufacturing processes and gaining perspective on various dimensions that enable manufacturers to access effective predictive technologies	GA and ANN	SL	Cost function	Manufacturing operation	Smart Manufacturing
Source	Objective	Algorithm Main Algorithm	Supervision	Inputs	Outputs	Application Domain
(Hodonou et al., 2020)	Developing a new methodology for manufacturing process selection based on fuzzy logic	Fuzzy logic	SL	Manufacturing cost, environmental impact	Performance indicator	Production of aircraft components
(Dohale et al., 2021)	Generating a compatible production system with ML for any manufacturing firm	An integrated three-stage Delphi-MCDM-BN framework	SL	Market needs, competitive priority, monetary investment in resources for the production system	Suggestion of a suitable production system	–
(Simeone et al., 2021)	Developing an intelligent decision-making support system to offer a simple solution for customers in a cloud manufacturing system	Three-layered feed-forward NN	SL	Surface utilization rate, processing time, deadline compatibility	Rank of manufacturing processes according to customer profile	Cloud framework manufacturing for sheet metal cutting
(Zhao et al., 2022)	Developing a novel framework for identifying process sequences used to manufacture a discrete part	PrefixSpan Algorithm	SL	STL file, material properties, quality requirements, manufacturing sequence	Sequence manufacturing pattern	–
(Y. Zhang & Fiona, 2022)	Designing a hybrid ML-assisted, web-based automated manufacturability analyser and recommender for additive manufacturing	Hybrid sparse CNN	SL	Material type, material density, printing speed, layer thickness, infill percent, adhesion type, nozzle temperature, bed temperature, scale	Printability status	Manufacturability for AM

Table 4. Classification of ML support in manufacturing monitoring articles.

Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(Saxena & Saad, 2007)	Developing near-optimal design parameters of diagnostic systems for condition monitoring of mechanical systems	GA and ANN	SL	Vibration signals, rotational speed, radial load	Bearing and gear condition	Rotating mechanical systems
(C. Shao et al., 2013)	To increase the precise process knowledge for feature selection and parameter tuning in quality monitoring of manufacturing processes	KNN	SL	Features are defined in the study according to the inspected case study	Welding quality	Ultrasonic metal welding
(Grasso et al., 2017)	Developing a methodology to detect and identify defects during the layer-wise process in the visible range by a machine vision system	PCA and K-means Clustering	UL	Images of each printed layer	Defect regions	SLM
(Das et al., 2017)	Developing an effective methodology for internal defect identification by combining statistical features like asymmetry, dispersion, and excess for the friction stir welding process	SVM, SVR, ANN	SL	Tool rational speed, welding speed, shoulder diameter	Weld status (either defect-free weld or defective weld)	Friction stir welding
(Ren et al., 2018)	Developing a new methodology for bearing remaining useful life prediction based on DL	DNN	SL	Frequency domain features, autoencoder-time features, and time-frequency domain features extracted from vibration signals	Remaining useful life	Bearing manufacturing
(Godreau et al., 2019)	Developing a new data mining method for the continuous improvement of high-speed machining	Contextual Clustering	UL	Vibration signals, the ID of the tool and workpiece program, spindle power, actual spindle speed, feed rate	Tool condition	High-speed machining
Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(Okaro et al., 2019)	Developing an automatic fault detection in AM products with ML	Semi-SL	Semi-SL	UTS, the x-y position of the laser, projection vectors of positions	Accept or reject the part	LPBF
(B. Zhang et al., 2019)	Developing a CNN based model to investigate the porosity data for laser AM process	CNN	SL	Coaxial images of melt pool	Porosity attributes	Laser AM
(Martínez-Arellano et al., 2019)	Developing a new big data approach for tool wear classification based on DL and signal imaging which avoids pre-processing or filter methods	CNN	SL	Force signals, images	Tool condition	Dry milling
(Pratama et al., 2020)	Developing a new perspective for online tool condition monitoring based on a novel ensemble classifier	Ensemble Classifier	SL	Cutting speed, feed rate, depth of cut	Tool condition (wear type)	–

(*Continued*)

Table 4. (Continued).

Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(Nasir & Cool, 2020)	Developing a hybrid ML model by using the combination of vibration signals and self-organizing maps for the prediction of cutting power and waviness in the circular sawing process of Douglas-fir wood under very high feed speed conditions	Adaptive neuro-fuzzy inference system, self-organizing map-based NN	SL and UL	Cutting power and corresponding vibration signal for 1 second of cutting	Average cutting power and waviness	Wood machining
(Song et al., 2020)	Developing a new novel approach for determining the wear state of a milling cutter based on clutter signal of spindle current	Deep CNN	SL	Spindle vibration acceleration signals and spindle current signals	Wear status recognition for the milling cutter	Milling
(Gülçür & Whiteside, 2021)	Presenting quality proxies or process fingerprints work in the first place and improving with an additional layer of instrumentations using more quality indicators	Multiple Linear Regression	SL	Piston position, injection pressure, melt temperature, mould temperature, injection velocity, switch-over pressure, packing pressure, packing duration	Microreplication efficiency	Micro-injection moulding
(Xie et al., 2021)	Developing a novel method for accurate and automatic tool wear state identification	Least Squares SVM	SL	Vibration values in X, Y, and Z direction	Milling tool flank wear values	Milling
Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(Kubik et al., 2021)	Developing an SVM to classify abrasive wear states on blanking operation based on transformation, pre-processing, and data acquisition	SVM	SL	Punch force, stroke speed, sensor type	Wear States	Blanking and sheet metal forming
(J. B. Wang et al., 2022)	Cutting force embedding for applications in feature selection for having a better performance for condition monitoring of cutting tools	Manifold Learning	UL	Depth of cut, spindle speed, feed rate, vibration signals, cutting force	Tool condition (wear)	Vertical machining centre
(Sandru et al., 2022)	Developing a methodology for modelling the dependency of the device performances under the influence of technology parameters at early stages	Bayesian Optimization, Regression, and NN	SL	Process control parameters	Electrical parameters	Analog circuit manufacturing
(Mei et al., 2022)	Developing an extendable relative degree of contribution-based feature selection methodology was proposed to identify optimal feature combination	DNN	SL	Pressure, motor power, volume flow, temperature, vibration, efficiency factor, cooling efficiency, cooling power	Cooler condition, valve condition, internal pump leakage, hydraulic accumulator	Machinery

(*Continued*)

Table 4. (Continued).

Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(Sun et al., 2022)	Developing an ANN algorithm for status monitoring and milling cutter wear prediction	ANN	SL	Velocity, sound, high-frequency energy signal, current, cutting depth, rotating speed	Healthy, slight wear, significant wear	Milling
(Mahmood et al., 2022)	Developing a high-quality tool wear detection system	PCA	UL	Cutting parameters for different tools, spindle speed, feed rate, type of tool, coolant, working angle of the tool, etc.	Type of the tool wear	Drilling

Table 5. Classification of ML support in Quality Control Articles.

Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(Kankar et al., 2011)	Developing a classification of ball bearing faults by using NN and SVM	NN and SVM	SL	Vibration signals, rotational speed, bearing condition, number of loaders	Bearing fault type	Machining for ball bearing production
(Lieber et al., 2013)	Prediction of the physical quality of intermediate products in interlinked manufacturing processes	KNN and DT	SL and UL	Rolling force, rolling speed, and temperature	Quality level and end dimensions of steel bars	Rolling mill process
(Strasser et al., 2018)	Developing an ML algorithm for selecting variables, building and evaluating models for adaptive parameter settings in manufacturing processes	ANN, LR, cross-validation, square mean error	SL and UL	Dimension of each part in each step, the weight, temperature, pressure, and forces applied to the produced part	Quality measures	–
(Escobar & Morales-Menendez, 2018)	Developing a pattern recognition strategy to detect rare quality events.	LR, HCR, ReliefF	SL	Feature correlation matrix, correlation threshold, list of conditional probabilities	Parsimonious predictive model containing the most relevant quality features for the product	–
(D. Wu et al., 2018)	Predicting the surface roughness of the products manufactured with FDM	RF, SVR, RR, least absolute shrinkage, and selection operator (LASSO)	SL	The temperature of the build plate, the temperature of the extruder, the vibration of the build plate, the vibration of the extruder, the temperature of the deposited material	Predictions of surface roughness	FDM
(Scime & Beuth, 2018)	Developing a CNN algorithm for autonomous detection and classification of anomalies occurred during manufacturing	CNN	SL	Images of defected parts	Detected anomalies	LPBF
(Peres et al., 2019)	Application of Predictive manufacturing system solution into quality control in the automotive industry	Gaussian NB, KNN, DT, Random Forest, SVM	SL	Dimensional features	Each car part labeled as OK or NOK	Automotive Manufacturing
(Hanhirova et al., 2019)	Designing a defect detection ML system to detect power cable surface defects	CNN	SL	Cable outer diameter	Cable surface defects	Extrusion for power cable manufacturing

(*Continued*)

Table 5. (Continued).

Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(Mahmoudi et al., 2019)	Developing an anomaly detection framework for the LPBF process to distinguish process deviations by using thermal signatures	Gaussian regression and SVM	SL	High-speed thermal images of parts	Places of defects	LPBF
(Papananias et al., 2020)	Developing a new method called inspection by exception: used to decrease the inspection of produced parts	Fuzzy C-means clustering	UL	Material conditions, tempering temperature, vibration, and force signals of the metal-cutting process	Determination of parts that should be inspected	Metal manufacturing
(Z. Zhang et al., 2020)	Developing of a real-time defect identification method for Al allows using arc optical spectroscopy and an integrated learning method for the robotic arc welding process	PCA and RF	SL and UL	Fe I spectrum for wire feeding detection, H I spectrum for porosity detection, AR I spectrum for penetration detection	Normal seam, coupled defects, wire stuck, surface contamination, inner porosity, under penetration	Robotic arc welding for Aluminum alloys
(Cho et al., 2020)	Predicting the quality of plastic products manufactured with extrusion	LR, SVM, RF, Bagging method	SL	Extrusion temperature, extrusion speed, external temperature, water temperature, screw speed, die temperature, cylinder temperature, external humidity	Quality of extruded parts	Plastic Extrusion Process
(Finkeldey et al., 2020)	Developing a novel ML-based methodology to predict quality characteristics of the injection molding process for different process parameters	DT, Least Absolute Shrinkage and Selection Operator	SL	Nozzle contact diameter, cooling channel diameter, mold width, mold depth, mold length	Cavity pressure, injection pressure, flow rate, thickness, weight	Injection molding for plastic products
(Bauhofer & Daraio, 2020)	Developing a semi-empirical numerical model to predict shrinkage-driven distortions in direct laser writing	ANN	SL	Fabrication parameters, material parameters, modelling parameters	Elastic strain energy	Direct laser writing
(T. Wang et al., 2020)	Developing a feature extraction methodology to improve the detection of faulty and abnormal situations	Kernel PCA	SSL	BC3 flow, Cl2 flow, pressure, load, tuner, power	Fault type	–

(*Continued*)

Table 5. (Continued).

Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(X. Zhang et al., 2020)	Analyzing the defect count data observed in steel products based on high overdispersion and nonnegative integers	RF	SL	Slab width, slab length, slab thickness, region of the slab, casting speeds, argon flow index, rolling temperature, the quantity of constituent, rolling width, rolling length, plate thickness, plate width, plate length, plate weight, heating index, annealing time, annealing temperature, in-mold EMS, EMS current index, steelmaking code	Number of defects	Casting, rolling, machining of steel
(Denkena et al., 2021)	Developing an essential approach with ML for achieving a correlation between process parameters and measured surface quality	SVM	SL	Tool feed rate, inclination angle, depth of cut, cutting speed	Roughness of the workpiece	Polishing process
(Leco & Kadirkamanathan, 2021)	Reducing total inspection time with the GPR model to predict part quality through in-process sensors	Gaussian Process Regression	SL	Depth of cut	Prediction of inspection results	Robotic machining
(Bak et al., 2021)	Developing a prediction algorithm for better product quality for the die-casting process	Shallow NN	SL	29 manufacturing parameters, some of which are: molten metal temperature, room temperature, humidity, metal pressure, valve gate open, low acceleration position, low speed	Product Quality	Die-casting for Aluminum
(W. Guo et al., 2021)	Estimating accurate surface roughness in the grinding process and providing feasible monitoring scheme for other manufacturing operations	Recurrent NN and Long short-term memory network	SL	Grinding force, vibration, acoustic emission signals	Surface roughness	Grinding of steel products
(Yan et al., 2021)	Developing a deep transition model with multi-task learning to predict all output sensing variables according to the sequential production line structure	DNN-based multistage multi-task learning	SL	Process sensing variables	Product quality sensing variables	Multistage manufacturing systems
(Charalampous et al., 2021)	Developing a novel method for process parameter selection for improving the dimensional accuracy of manufactured specimens with FDM	Regression modelling	SL	Layer height, printing speed, and printing temperature	Geometrical dimensions in height, depth, and thickness	FDM

(*Continued*)

Table 5. (Continued).

Source	Objective	Algorithm: Main Algorithm	Algorithm: Supervision	Algorithm: Inputs	Algorithm: Outputs	Application Domain
(X. Zhang et al., 2021)	Improving the adaptability of the scale changes of surface defects of solar cells	CNN	SL	Defected solar cell images	Crack type and crack place on the solar cell	–
(Kahng & Kim, 2021)	Developing a SSL-based methodology to improve the performance of wafer bin map defect pattern classification	SSL	SSL	Five data augmentation: cropping, cut-out, rotation, shifting, and noise addition	Labeled class: center, donut, edge-ring, edge-loc, loc, scratch, near-full, random, none	Wafer bin map for semiconductor manufacturing
(Reséndiz-Flores et al., 2022)	Finding an optimal solution for misclassification of variable screening purposes	Kernel-based Mahalanobis-Taguchi system, sequential feature selection, RF	SL	Day tank temperature, level, pump pressure input, recirculation flow, head pressure	Three cases of variable selection	Foam injection and welding
(Tian et al., 2022)	Improving prediction accuracy of broad learning system for surface roughness prediction	Broad learning system with binary grey wolf optimization	SL	Depth of cut, spindle speed, feed rate	Surface roughness	Slot milling
(Guo & Guo, 2022)	Increasing fault detection rates of MTS with BOW feature extraction		MTS based on BOW	SL	Bag-of-words set	Extracted features for fault detection
(Xu et al., 2022)	Developing a self-supervised high-efficiency defect detector methodology that uses image segmentation		SSL	SSL	Defected images of surface defects	Highlighted image of the surface defect
(Z. Liu et al., 2022)	Developing a methodology for metal surfaces with a few-shot defect recognition methodology	Attention embedding network, multi-resolution cropping SSL	SSL	Defected images	Highlighted image for the defect	Few-shot defect recognition

(*Continued*)

Table 5. (Continued).

Source	Objective	Algorithm				Application Domain
		Main Algorithm	Supervision	Inputs	Outputs	
(Link et al., 2022)	Developing a general ML methodology for creating quality prediction models by using small datasets to predict surface roughness as a function of five process variables	Shape-constrained Regression	SL	Diameter of abrasive grits, cutting time, number of revolutions of brush, number of revolutions of the workpiece, cutting depth	Arithmetic-mean surface roughness	Surface roughness prediction for the Brushing process
(Manivannan, 2022)	Developing an ensemble-based CNN semi-supervised approach for wafer bin maps image classification	CNN	Semi-SL	Spatial defect pattern images	Defect patterns	Wafer bin map pattern detection
(Chu et al., 2022)	Developing a morphological feature transformation for 3D wafer bin maps for defect recognition	NN	Semi-SL	3D visuals of defect patterns	Defect patterns	Wafer Defect Recognition

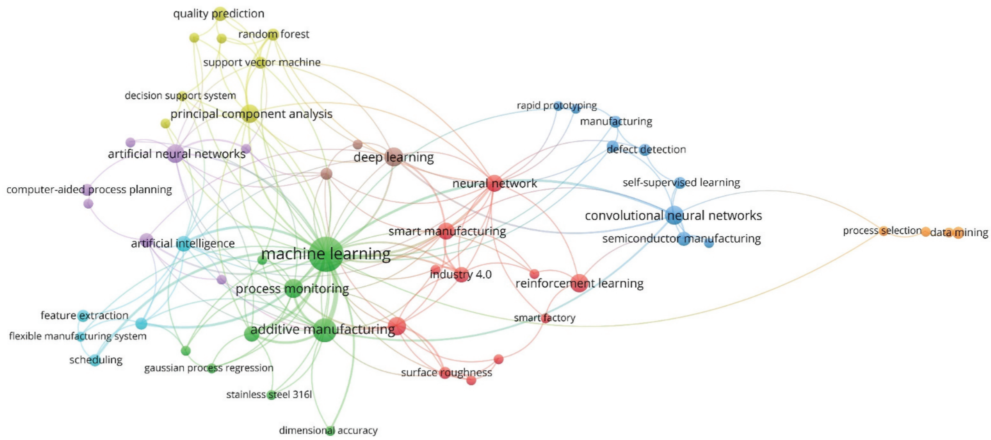

Figure 4. Keyword co-occurrence analysis using VOSviewer.

algorithms offer to handle job shop scheduling with strict time constraints using RL (Altenmüller et al., 2020). One of the most crucial performance indicators of production scheduling is the make span. It is directly linked to the schedule or the timetable and the cost of the production process (De Jong et al., 2019). Consequently, ML algorithms utilize the high dimensional data for production scheduling and planning while considering multiple objectives such as reducing production costs, minimizing the make span, balancing the workload, increasing flexibility, reducing human effort (J. Li et al., 2022), enhancing rescheduling capacity, and improving dynamic scheduling (Abidi et al., 2020).

The classification of reviewed articles that include production scheduling and planning is presented in Table 2. In short, a well-developed ML-based system can match the requirements and characteristics of modern manufacturing systems, in that it increases the efficiency of production scheduling. This is often done by trying to increase the concurrency between tasks for complex scheduling.

3.3. Manufacturing process selection

Selecting the most suitable manufacturing technology for developing new products plays a critical role in the production industry since it affects the product's quality, cost, and production time (Ördek et al., 2022; Ördek & Borgianni, 2023b). Traditionally, manufacturing process selection has relied on human supervision, which requires proper training (Hoefer & Frank, 2018). However, heavy reliance on human knowledge and the use of engineering drawings prevented automated optimization and led to low efficiencies in this manufacturing function. The available software technologies are limited in their support to manufacturing process selection due to rule-based implementations (Hamouche & Loukaides, 2018). According to Dohale et al. (2021), selecting the most suitable manufacturing process is essential for a manufacturing firm to compete with other companies and achieve business success. Furthermore, sustainability plays an increasing role in selecting the most suitable manufacturing technology for a product, which represents another dimension to consider. A manufacturing system's sustainability evaluation is based on various metrics based on the environment, society, and economy (Jayawardane et al., 2023). ML algorithms can support process selection by evaluating manufacturing processes to minimize raw material and machine usage. Hence, they can improve production time and reduce energy and waste material usage (Marini & Corney, 2019). ML algorithms can be used in decision-making for AM processes to analyse the manufacturability of a product and to select a specific AM process (Y. Zhang & Fiona, 2022). Because of the number and variety of objectives, requirements, and constraints, using ML algorithms to select the most appropriate manufacturing technology can lead the following advantages:

- ML algorithms have the possibility to minimize the need for human supervision,
- ML algorithms have advantages in flexibility compared to rule-based software,
- ML algorithms can manage a large number of different parameters,
- ML algorithms can be fast, accurate, and time-efficient.

In short, ML algorithms can improve and shorten the manufacturing technology selection process significantly, even without human supervision (Dohale et al., 2021). In this function, geometrical properties (Marini & Corney, 2019), material type and properties (Zhao et al., 2022), cost of production (Ghahramani et al., 2020), environmental impacts (Hodonou et al., 2020), manufacturing conditions, and images (Ördek & Borgianni, 2023a) are typically used as inputs to train ML algorithms. The detailed classification of ML support in manufacturing process selection is provided in Table 3.

3.4. Production monitoring

Production monitoring has a crucial role in manufacturing since it ensures efficiency and effective functioning of a manufacturing process or a production line. It operates to identify and rectify issues in real-time. This positively affects productivity and reduces costs (Song et al., 2020; Xie et al., 2021). Automatic production monitoring is required for complex manufacturing processes where people's response time is too long or beyond human capabilities. In addition:

- Manual condition monitoring is expensive,
- Manual inspection may result in errors, and it usually depends on the experts' opinions,
- It is slower than an automated system.

Moreover, the following reasons were a trigger for the introduction of ML in production monitoring. Condition monitoring research includes investigating tool condition, workpiece condition, and safety (Sun et al., 2022). Tool condition monitoring constitutes a large part of the research conducted in this manufacturing function since machine tool costs represent the highest expenses in production lines (Sun et al., 2022). In modern manufacturing systems, tool failures correspond to 20% of the downtime, which causes a tremendous loss of profits for a production company (Martínez-Arellano et al., 2019). The main source of tool wear is the inevitable friction between the tool and the workpiece (Xie et al., 2021). The type of tool wear is also considered an essential information to gather in production monitoring since the wear type affects the quality of the produced parts (Mahmood et al., 2022). The essential parameters used in this manufacturing function are spindle speed, depth of cut, feed rate, vibration signals, rotating speed, and cutting force (J. B. Wang et al., 2022). Real-time condition monitoring and accurate assessment of the tool wear status can reduce production costs and improve the useful life of machining tools.

Modern condition monitoring operations include various sensors used to collect data on the operating machines. The scale of this data is significant, and connections between these sensors may show redundancies (Mei et al., 2022). To be able to find the connections and interpret sensor data, ML algorithms are suitable and required since they can operate with a large amount of data and point out unexplored connections. As a result of the classification conducted, ML algorithms are promising tools for enhancing production monitoring. The central performance criteria in condition monitoring is the ability of ML algorithms to provide close to real-time evaluations and corrective actions using reduced computing power. The detailed classification of the articles that include the monitoring function of manufacturing is presented in Table 4.

3.5. Quality control operations

Based on the current review results, ML support in quality control is the most researched and investigated manufacturing function among the ones considered here. This manufacturing function ensures compliance with standards and production parameters.

Traditionally, certified experts have conducted quality control on a randomly selected production batch. The quality control inspection process cannot usually reveal all the production faults because human experts cannot keep the high-intensity work for extended times (T. Wang et al., 2020). With the development of sensors, this problem is partially solved since the sensor data can be high-dimensional, large, and noisy, requiring a ML system to manage and extract meaningful data (Yan et al., 2021). ML algorithms can be used to reduce the dimensionality of input parameters in this function to improve processing time, reduce the computational cost, and, in some cases, improve computational performance (Reséndiz-Flores et al., 2022). Moreover, product dimension variability, the random nature of uncertainties, and disturbances during manufacturing are some of the most challenging aspects of quality control (Peres et al., 2019). By using ML algorithms, it is possible to overcome these problems and achieve an effective quality control operation.

ML algorithms are beneficial for quality control function because they can:

- Replace human experts with better performance (T. Wang et al., 2020),
- Predict quality problems early and work with high-dimensional data (Yan et al., 2021),
- Boost quality and have high performance in predicting product failures (Z. Y. Liu et al., 2022),
- Detect and analyse defects for various manufacturing technologies (Scime & Beuth, 2018),
- Distinguish naturally occurring surface imperfections from significant defects (Hanhirova et al., 2019).

This function is essential in product development and manufacturing since it checks the accuracy of the manufactured parts based on various parameters and elements. ML algorithms are used to support this function in order to organize operations, predict and avoid faulty products. The overall classification of ML support in the quality control function of manufacturing is available in Table 5.

4. Discussion

The present review on the use of ML support in manufacturing technologies presents a very active and extensive field of research, with a large number of niche applications. Those applications share limited similarities and confirm the flexibility of ML methods. Research groups appear to work in isolation and on specific problems. Synergetic research in the field did not clearly emerge, which makes the research in the field appear fragmented. New ML-based proposals are continuously developed and building on past research is not frequent. Some reasons can explain this situation.

(1) Few contributions made the developed algorithms publicly available.
(2) Some applications might have been developed for peculiar issues of a specific manufacturing company. In this case, generalizability of the issues can be limited, as well as full divulgation of the results might be complicated by disclosure problems.
(3) Some applications might have resulted as an attempt to apply ML with limited concern of real needs in manufacturing, see the aforementioned hypothesis of technology-push predominance. Therefore, the intrinsic scope of these applications is to demonstrate the possibility of implementing ML, which poorly helps build a systematic introduction of ML in manufacturing to facilitate companies' work. In this circumstance, the aim to link these applications with other proposals is clearly secondary.

The discussions that follow aim to outline similarities across the studies, misalignments, and chances for the synergic use of the developed ML-based algorithms. This is intended to make the support of the engineering dimensions of the manufacturing process broader and more impactful.

4.1. Scope and outreach of the machine learning support in the reviewed contributions

One of the most noteworthy outcomes of the current review is that most articles included in this review are mono-functional, i.e. they focus on a specific and limited manufacturing function. Few can be attributed to two manufacturing functions (property prediction and quality control); these are classified based on the core manufacturing function supported, hence they are found in one table only. For example, Radetzky et al. (2019) used a hierarchical DT-based algorithm to predict parameter properties for the grinding process. The predicted parameters were the surface roughness of grinded products. H. S. Park et al. (2021) also proposed an ML -based DNN algorithm to predict the density ratio and surface roughness of Ti-6Al-V4 SLM-fabricated parts. This research can be classified in both property prediction and quality control functions of manufacturing since the methodology offers the prediction of not only material properties but also quality properties. J. Wang et al. (2022) proposed an UL algorithm to improve cutting tool condition monitoring by applying feature selection. The outcome of the algorithm was the condition of the cutting tool; however, the methodology also dealt with property prediction. Therefore, this research (J. Wang et al., 2022) can also be listed under the property prediction function of manufacturing. Sandru et al. (2022) proposed a regression-based ML methodology to model the dependency of device performances under the influence of technology parameters. This article is categorized under the production monitoring function; nevertheless, it also involves the property prediction function since the methodology presented in the research predicts the electrical properties of analogue circuits. Charalampous et al. (2021) proposed a regression-based ML algorithm to select the optimal process parameters for improving the dimensional accuracy of produced specimens. Although the research included property prediction, the main application was quality control, and, as such, it is found in Table 5.

4.2. Similarities of inputs/outputs and possible links among independently developed algorithms

Some articles showed similarities in terms of ML outputs. This can be interpreted as the relevance of such outputs for manufacturing processes and the concurrent development of multiple ML algorithms, which, in the authors' view, can be motivated by

- different conditions or domains for the determination of these outputs;
- need to improve the algorithms' performance;
- refinements of previously proposed algorithms, typically by the same research group.

Mechanical properties of the produced products were predicted in several articles. For instance, both R. Liu et al. (2015) and Herriott and Spear (2020) used ML to determine the yield strength of microstructures. SL algorithms were applied in both articles to achieve mechanical property prediction. Although the inputs of both articles were different, the predicted outcome of both methodologies was similar. In some articles, similar ML methodologies were used to predict stress, strain, and elastic modulus for products manufactured with different technologies (Kopper et al., 2020; Wanigasekara et al., 2020). Several articles analysed and predicted the make span during a manufacturing operation (De Jong et al., 2019; X. Shao & Kim, 2021; Tan et al., 2019). Tool condition monitoring was also commonly investigated among the articles that are included in the current review. These articles usually studied the wear status of machine tools in several machining operations: high-speed machining (Godreau et al., 2019), milling (Martínez-Arellano et al., 2019; Song et al., 2020; J.; B. Wang et al., 2022), metal turning (Pratama et al., 2020), and blanking (Kubik et al., 2021). Furthermore, C. Shao et al. (2013) and Das et al. (2017) worked on production monitoring to identify the weld status of the welding manufacturing operation. In the quality control function of manufacturing, the most commonly investigated quality feature was the prediction of surface roughness (Denkena et al., 2021; W. Guo et al., 2021; Tian et al., 2022; D. Wu et al., 2018). Different manufacturing technologies were investigated based on the production requirements of surface roughness. Four technologies were investigated with SL to predict the surface roughness: polishing (Denkena et al., 2021), FDM (D. Wu et al., 2018), grinding (W. Guo et al., 2021), and slot milling (Tian et al., 2022). Three of these articles shared similar algorithm inputs, namely machining parameters such as depth of cut, cutting speed, and feed rate (Denkena et al., 2021; Tian et al., 2022). SSL applications in quality control used defected surface images of manufactured parts as input to highlight the defect area as the output (Z. Y. Liu et al., 2022; Xu et al., 2022). Semi-supervised based NNs were used to detect the defect patterns in wafer bin manufacturing operations by using images as inputs (Chu et al., 2022; Manivannan, 2022). Chu et al. (2022) and Manivannan (2022) used a similar methodology to generate NN-based algorithms to identify the defect patterns with 3D and 2D map images of a wafer bin as inputs, respectively.

The similarity of inputs can be ascribed to the typically large availability of same kinds of data. At the same time, similarities between outputs of a preceding manufacturing function and inputs of a subsequent function highlight chances for integrating algorithms or making them work sequentially.

In this respect, monitoring and quality control functions show similarities among the inputs and the outputs of ML algorithms as evident by comparing Tables 4 and 5. While the monitoring function deals with the tool life in a machining process, the quality control function is used to ensure that machined parts fit the acceptable quality range. Thus, these two functions could be potentially supported contextually and it is possible to develop an ML algorithm for their combination. Moreover, in some cases, parameter selection was used to determine quality measures (Strasser et al., 2018) and fatigue life (M. Zhang et al., 2019), which are investigated under the quality control function too. This shows an additional example where a potential combination could enable the fulfilment of multiple functions simultaneously.

4.3. Supervision

Figure 5 Shows the classification of articles included in this review based on the ML algorithms and manufacturing functions. Here, it is worth pointing out that most ML algorithms used to support manufacturing are based on SL. Hence, articles that use SL require labelled data, which arises as a limitation for the industrial use of these systems. This issue is discussed in the section named as 'Limitations of using Machine Learning in Manufacturing' in detail. Several articles (Barrionuevo et al., 2021; Cho et al., 2020; Herriott & Spear, 2020; Sandru et al., 2022; B. Wang et al., 2022) have applied various ML algorithms to the same problem to determine the optimal ML approach among a set of alternatives. These were applied to assess and compare the performance of different ML algorithms, thus contributing to the identification of superior methods within the respective studies.

Moreover, in Figure 5, in line with the previous reviews on the topic (Mypati et al., 2023; Nti et al., 2021; Paturi & Cheruku, 2021) and other examples in engineering and neighbouring fields (Bertolini et al., 2021), ANN-based algorithms are the most common ML applications in the article set. This is supposedly due to the fact that ANNs are computational models that imitate the human brain and are practical for various applications. With the exemption of RL algorithms, it appears that all other algorithms are distributed equally across the various manufacturing functions (See Figure 5). As seen in Figure 5, RL algorithms are almost exclusively found in articles categorized under the domain of production scheduling and planning. This is likely due to the working principle of RL that can learn from historical data to optimize schedules in real-time (J. Li et al., 2022).

4.4. Advantages of using machine learning in manufacturing

The analysis of the collected articles revealed some significant advantages concerning ML support in manufacturing. The focus, here, is on functions whose fulfilment would be strongly impractical or nearly impossible without ML or other AI systems. These key advantages include:

- Predictive maintenance: ML algorithms can analyse sensor and historical data to predict tool failures before they occur (Godreau et al., 2019; Mahmood et al., 2022; Pratama et al., 2020; Song et al., 2020; Sun et al., 2022; J. B. Wang et al., 2022; Xie et al., 2021).

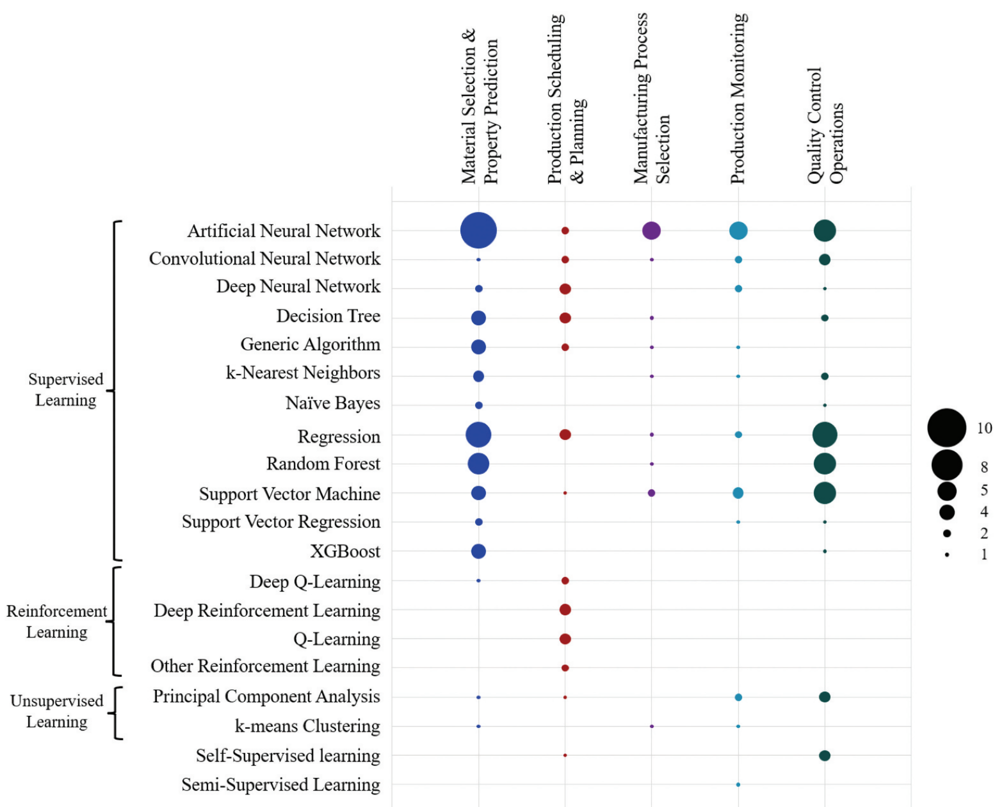

Figure 5. Number of article distribution based on ML algorithm, supervision, and manufacturing function.

- Quality control: ML algorithms can detect faults on production lines using real-time data collected with cameras or sensors. They can identify anomalies or defects in products, ensuring high-quality production, hence reducing manual inspections (Chu et al., 2022; Z. Y. Liu et al., 2022; Manivannan, 2022; Xu et al., 2022; X. Zhang et al., 2021).
- Process optimization: ML algorithms can analyse complex manufacturing processes and identify areas for optimization. Manufacturing operations can be enhanced by adjusting parameters (temperature, speed, pressure, or cutting speed in real-time) in real-time. Hence, efficiency can be enhanced and resources can be utilized (Radetzky et al., 2019; Torquato et al., 2021; B. Wang et al., 2022).
- Process automation: ML can support the labour-intensive tasks by automating repetitive tasks to release human resources for more creative and complex tasks (Dohale et al., 2021).
- Human-machine collaboration: Human and ML collaboration can improve decision-making and the efficiency of a task in a manufacturing process (Gonzalez Rodriguez et al., 2020; Simeone et al., 2021; W. Wu et al., 2021).

4.5. Limitations of using machine learning in manufacturing

Although ML algorithms provide accurate, quick, and adaptive applications, they also have several limitations. Data collection is the major limitation of ML algorithms that support manufacturing. Despite the rapid increase in available data, problems may occur such as format inconsistencies, poor data quality, and different standards (Al-Abassi et al., 2020). The available manufacturing data can contain high dimensional data with irrelevant and redundant information, which may have a strong influence on the performance of the algorithms (Wuest et al., 2016). Another major limitation is the need for pre-processing or manual labelling, which plays a vital role in the generation of ML algorithms since it strongly affects the performance of the algorithms, especially with SL. Depending on the amount of data used to train the ML algorithms, the process of cleaning, normalizing, and transforming data can be extremely time-consuming (Wuest et al., 2016). However, suitable tools are available that support the most common pre-processing applications, such as normalizing, filtering, and resizing (Pham & Afify, 2005).

Moreover, overfitting is a significant limitation while training an SL algorithm. It can cause poor performance and difficulty in interpreting the model (Bu & Zhang, 2020). A growing concern in ML applications is to obtain the required labelled data for training an SL algorithm. This creates difficulties while training a new algorithm since data labelling is expensive and time-consuming (Asano et al., 2019). Two solutions have been investigated so far in the literature to solve the data labelling problems. One considers unsupervised learning methods to avoid data labelling and utilize the available unlabelled datasets. Another alternative is to develop ML algorithms specifically for data labelling (Fredriksson et al., 2020, 2022; Silva et al., 2022).

5. Research opportunities for machine learning-supported manufacturing

Readers can visualize in Figure 3 the trend of the growing number of publications on ML-supported manufacturing, which looks exponential. As mentioned, it can be expected that many applications and proposals will be published in the coming years. The flourishing of the field does not guarantee standardization of practices, emergence of dominant systems, and the connection between different algorithms, which was posited in the previous section as a desirable output. Actually, at present, it is hard to assess the real impact the introduction of ML in manufacturing had on companies' capabilities and efficiency. Few articles witness large-scale diffusion and implementation of some algorithms. In the authors' view, data labelling arises as a major hurdle to accelerate the diffusion of ML in the manufacturing industry.

In this fast-evolving situation, research should be directed to maximize the practical achievements derived from ML-supported manufacturing. Since algorithms and learning mechanisms were attributed a major focus on the reviewed articles (see Figure 6), it can be hypothesized that the future development of the field could be driven by manufacturing exigencies rather than ML developments. The identification of these needs goes beyond the scope of this paper. Nevertheless, the authors believe that some opportunities offered by ML have not been adequately considered in the manufacturing field, even in relation to currently supported manufacturing functions. In this context, Figure 6 (details follow) summarizes the authors' reading of the reviewed literature, which direction ML supports in manufacturing could take, the remaining challenges, and which opportunities can be seized. Based on the literature, the manufacturing industry managed the functions discussed in this review using traditional methods provided in Figure 6. As mentioned throughout this review, the support of ML algorithms in manufacturing is

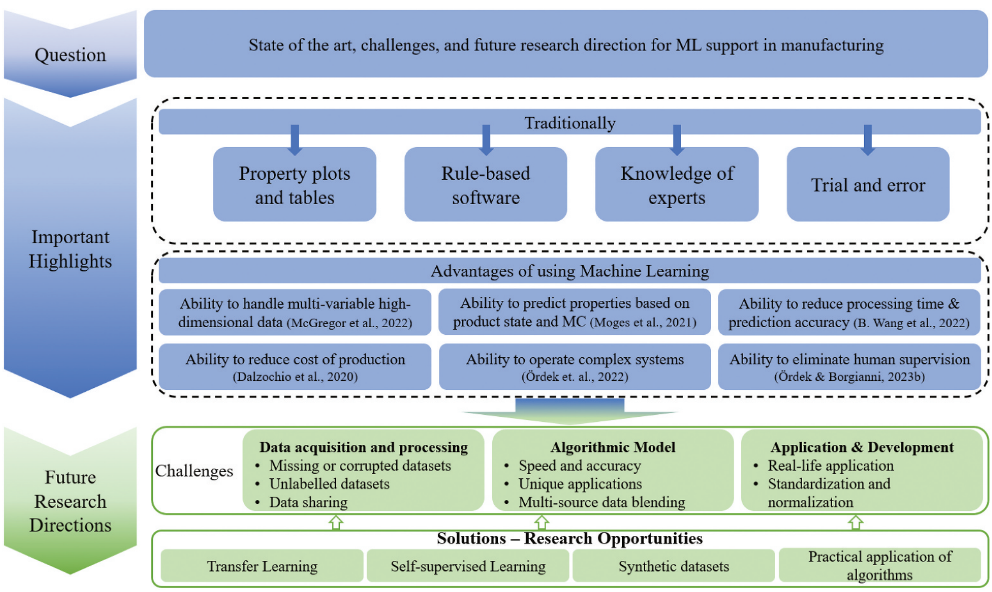

Figure 6. General overview of ML support in manufacturing.

increasing tremendously due to the advantages introduced by ML algorithms (See Figure 6) to automate and improve manufacturing operations. Nevertheless, although ML algorithms improve the performance of the manufacturing industry, some challenges are still to be addressed. These challenges arise as a result of the distinctive characteristics of both manufacturing processes and ML algorithms. The authors identified four fields that were deemed suitable for facing current challenges. These are explored in the following subsections to suggest future research directions, especially in consideration of the learning approaches that have been poorly capitalized on so far.

5.1. Transfer learning

One of the main assumptions in the majority of ML applications is that training and potential data must have the same distribution and feature space (Pan & Yang, 2010; Qin et al., 2022). However, with the development of industrial applications, it is unfeasible and expensive to retrain a model for each process or machine. Hence, the possibility of knowledge transfer becomes advantageous in this case. Transfer learning (TL) is used to improve ML models by transferring prior information or knowledge from a domain into

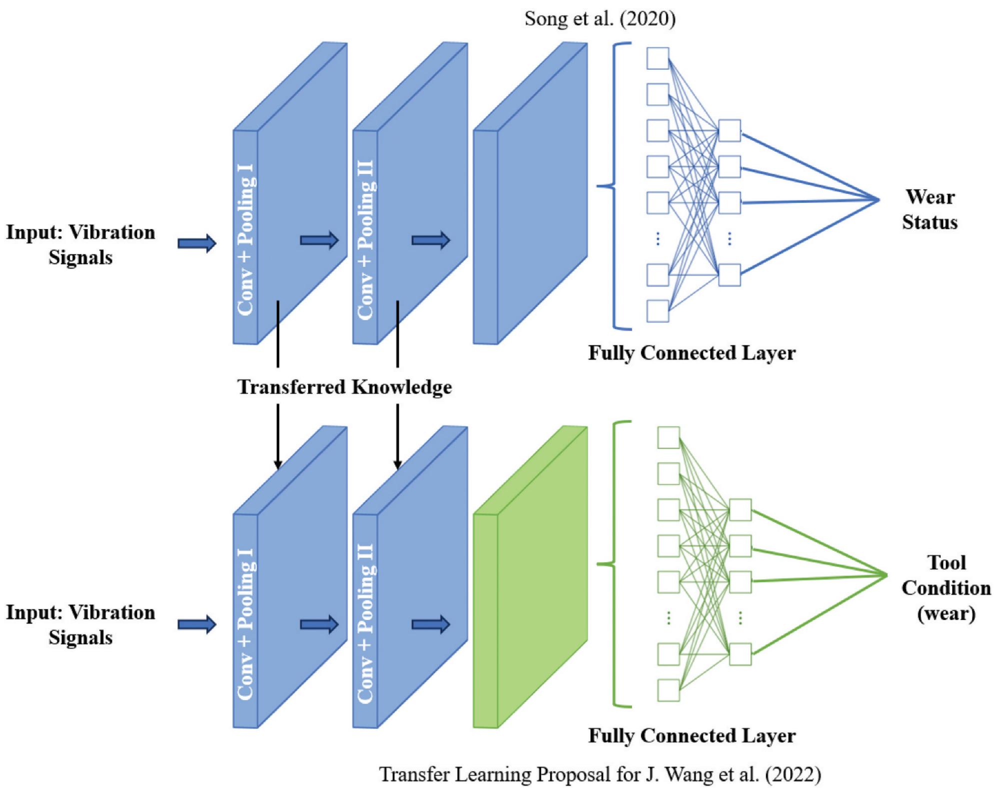

Figure 7. Possible scheme to use transfer learning to transfer knowledge from the research proposed by Song et al. (2020) to the study conducted by J. Wang et al. (2022).

another one (Pan & Yang, 2010; Weiss et al., 2016). A potential application of TL in the manufacturing domain follows.

J. B. Wang et al. (2022) and Song et al. (2020) worked on tool condition monitoring for vertical machining by using similar input data with SL and UL, respectively, as presented in Table 4. Song et al. (2020) used a deep CNN algorithm that can also be altered to transfer this algorithm in J. B. Wang et al. (2022) with the help of TL, as shown in Figure 7. Thus, this reduces the necessity to train an algorithm for the same purpose with similar input data.

Nevertheless, using TL in manufacturing is challenging because of the massive amount of unlabelled data. Overall, TL applications on manufacturing functions show great research potential since these enable the reduction of algorithm processing time and the transfer of models to various manufacturing processes. This, in turn, requires the definition of primitive model blocks that can be combined easily to form more complex ML models.

5.2. Self-supervised learning

SSL uses a semi-automatic process to obtain data labels by predicting unknown sections of the data based on the unlabelled input data. Specifically, the unlabelled data could be transformed, incomplete, corrupted, or distorted (X. Liu et al., 2021). Despite the high accuracy and success of SL and DL applications, the major reliance on labelled data brings several problems while training an algorithm. Data labelling creates a major problem in ML since it is expensive and time-consuming, especially in research areas that require a high amount of labelled data (e.g. manufacturing process selection and production monitoring) (X. Liu et al., 2021; Y. Liu et al., 2022). Another problem with a pure SL algorithm is over-fitting, which behaves well while training and badly with the test data (X. Li et al., 2019). The main advantage of SSL over UL is that the objective of the SSL algorithm is to recover unknown sections of the data that is still uncertain in supervised settings (X. Liu et al., 2021). For instance, based on the analysis conducted in the current review, C. Shao et al. (2013) and Das et al. (2017) worked on predicting weld status and quality, as presented in Table 4. These two studies used inputs based on

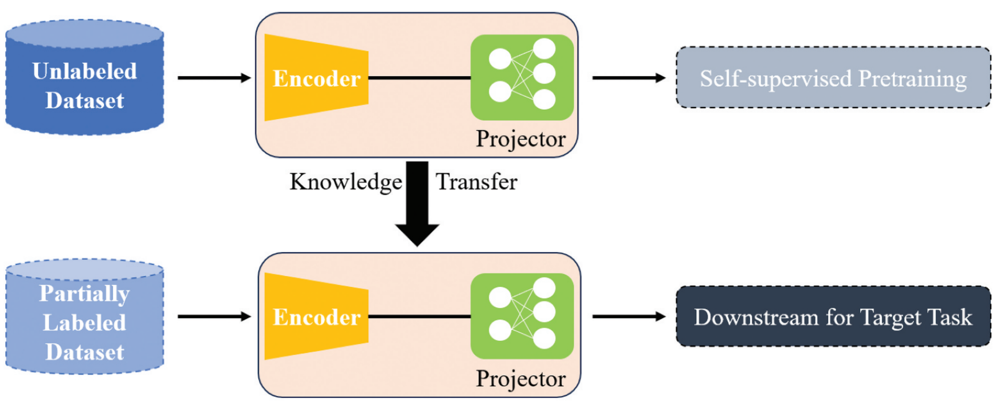

Figure 8. Working principle of a self-supervised learning algorithm.

machining and material properties. However, weld conditions can also be predicted by using images of welded parts (Ai et al., 2023). With the application of SSL, both weld images and machining properties, as well as material properties can be used to predict the weld status. The typical working principle of an SSL algorithm is shown in Figure 8. In the SSL pretraining stage, unlabelled images, such as those available in (Ai et al., 2023), can be used to train the encoder. In the downstream stage, the pre-trained knowledge is transferred to the encoder, which is trained to predict weld conditions. Hence, SSL applications in manufacturing process selection, production monitoring, and quality control can be explored to avoid the aforementioned problems.

5.3. Synthetic datasets

Successful ML algorithms require a huge amount of application of specific data that is difficult to obtain. In the manufacturing industry, the data can be collected from a real-life application or discrete-event-simulation (DES). The DES is used to generate synthetic datasets for specific operations (Denkena et al., 2014). The generated synthetic data can be utilized independently or in conjunction with the real data for ML training (Chan et al., 2022). This particular application can be beneficial for tool path optimization in AM processes. For example, a synthetic tool path dataset can be generated and used to train an ML algorithm to optimize the most suitable tool path for a specific AM technology. Using a synthetic dataset can improve the research proposed by Kim and Zohdi (2022) since having extensive input data significantly improves the performance of SL algorithms.

5.4. Practical applications of algorithms and other opportunities

Other relevant research opportunities can be explored. These are formulated based on the authors' examination of the reviewed articles and the identification of areas that, unexpectedly, were not dealt with.

The ML support for combining two or more manufacturing functions is worth investigating. For example, scheduling and monitoring functions can be combined to create a more advanced production schedule for scheduling maintenance operations for tools and machines. As aforementioned, most ML applications include SL, which uses labelled data for training. Hence, using a UL or SSL algorithm to study manufacturing functions with unlabelled data represents a research opportunity since unlabelled data increases daily.

Furthermore, most of the reviewed articles focused on a specific technology or subset of technologies that can also be applied to manufacturing process selection. While the use of ML in manufacturing is maturing, the ML is worth exploring support in manufacturing process selection with the consideration of both additive and traditional manufacturing technologies. In addition, the application of different ML algorithms for the same manufacturing function could be beneficial to select the algorithm that best suits the selected manufacturing function (Garouani et al., 2022).

6. Conclusions

The primary objective of this review is to provide a comprehensive view of ML support in manufacturing; a broad classification of 114 journal articles was made to this aim. Out of these articles, more than one hundred were not included in the earlier reviews with similar scopes, as documented in the methodological section.

In the literature, ML is classified based on the supervision of the data used during the algorithm generation. The most commonly used algorithms to support manufacturing applications are based on SL, and SL is followed by reinforcement, unsupervised, self-supervised, and semi-SL. This review classifies ML support in manufacturing in terms of inputs, outputs, and supervision of ML algorithms.

The analysis of the reviewed articles included the classification of ML applications in terms of material selection and property prediction, production scheduling and planning, manufacturing process selection, production monitoring, and quality control operations. For all these functions, the introduction of ML has given rise to tangible improvements despite residual issues in data processing and labelling.

The majority of articles included in the current review are mono-functional; namely, the ML application was restricted to a single combination of manufacturing process or control process and material. This aspect was seen as the main limitation of ML supports in manufacturing. A fundamental advancement is then the creation of algorithms that can cover a broader spectrum of applications with limited specialization. For this reason, the authors have identified TL as a major opportunity for a step change in the support of manufacturing enabled by ML.

The additional outcomes of the current review can be summarized as follows:

- The application of supervised and UL algorithms was sometimes juxtaposed. In this case, UL was used to pre-process the dataset, and SL was then applied to solve the actual problem.
- ML algorithms were generated with large amounts of data or a big dataset.
- Hybrid ML algorithms were also used to support manufacturing applications.
- Similarities were found among inputs and outputs of ML algorithms for different articles, which pave the way for potential future combined applications.

Overall, the authors see the following research opportunities as the most prominent; as such, these can be considered research recommendations for the scientific community:

- Generating algorithms covering multiple functions presented in this research.
- Exploring the potential benefits of TL in manufacturing applications.
- Considering the use of hybrid systems that implement SL and UL algorithms.
- Exploring the advantages of generating a synthetic dataset to improve the accuracy of ML algorithms.
- Investigating the use of SSL to overcome the necessary data labelling.
- Exploring ML applications to identify suitable hybrid manufacturing processes that combine additive and subtractive manufacturing.

List of abbreviations

AI	AI
AM	AM
ANN	Artificial neural network
Avg	Avg
Avg	Average
BOG	BOG
CNN	Convolutional neural network
DBN	Deep belief network
DES	Discrete-event-simulation
DL	Deep learning
DNN	Deep neural network
DQL	Deep q-learning
DQN	Deep-q-network
DRL	Deep reinforcement learning
DT	Decision tree
FDM	Fused deposition modelling
FIS	Fuzzy inference system
FMS	Fuzzy inference system
GA	Generic algorithm
HCR	Hybrid Correlation and Ranking
HDMD	High dimensional microstructure design
KNN	k-Nearest Neighbours
KRR	Kernel ridge regression
LPBF	Laser power bed fusion
LR	Logistic regression
MC	Manufacturing condition
ML	Manufacturing condition
MTS	Multivariate time series
NB	Naïve bayes
NN	Neural network
QL	Q-learning
PS	Photo spacer
PCA	Principal component analysis
RF	Random forest
RL	Reinforcement learning
RR	Ridge regression
RT	Regression trees
SL	Supervised learning
SLM	Selective laser melting
SVM	Support vector machine
SVR	Support vector regression
TL	Transfer learning
UL	Unsupervised learning
WGF	Weighted gaussian function

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