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Machine learning applications on IoT data in manufacturing operations and their interpretability implications: A systematic literature review

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A R T I C L E I N F O

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A B S T R A C T

Industry 4.0 has transformed manufacturing with real-time plant data collection across operations and effective analysis is crucial to unlock the full potential of Internet-of-Things (IoT) sensor data, integrating IoT with Artificial Intelligence (AI) techniques, such as Machine Learning (ML) and Deep Learning (DL). They can provide powerful predictions but anticipating issues is not enough. Manufacturing companies must prioritize avoiding inefficiencies, thereby developing improvement strategies from an Operational Excellence perspective. Here, the interpretability dimension of AI-based models could support a complete understanding of the reasons behind the outcomes, making ML and DL models transparent, and allowing the identification of the causal linkages between the inputs and outputs of the system. Within this context, this study aims first to deliver a comprehensive overview of the existing applications of Advanced Analytics techniques leveraging IoT data in manufacturing environments to then analyze their interpretability implications, referring to the interpretability as the description of the link between the independent and dependent variables in a way that is understandable to humans. Different gaps in terms of lack of full data enhancement are highlighted, providing directions for future research.

Introduction

The widespread adoption of emerging technologies (e.g. IoT) in the manufacturing sector is what is driving the move to the concept of Cyber Manufacturing, which is defined as a new manufacturing strategy that makes use of Industry 4.0 cutting-edge technologies [1]. The Industry 4.0 paradigm, born in 2011 at the Hannover Industrial Fair to describe the extensive usage of cutting-edge technologies in German industrial enterprises [2] includes Big Data Analytics, IoT, Cloud Manufacturing, Robotics, Additive Manufacturing, Augmented Reality, Modelling and Simulation, Cyber-Physical Systems, Cybersecurity and Block-Chain [3]. In fact, in recent years, enhanced manufacturing efficiency and effectiveness through technical agility have been attributed to this digital transformation. [4]. Indeed, manufacturing companies may get insights to optimize the efficiency of individual assets as well as the whole manufacturing process by applying Advanced Analytics algorithms to Industrial data [5]. The Industrial IoT, which is a key enabler of the Cyber Manufacturing concept, is used to integrate sensors, controls, and software platforms to enhance performance at the production unit and plant enabling real-time decision-making via ML techniques [6]. The main goal of adopting the Industrial IoT is to attain heightened productivity, improved operational efficiency, and advanced management of manufacturing processes and assets [7]. In this context, ML and DL algorithms can be the key to pursuing Operational Excellence and discovering hidden patterns in data collected through IoT sensors. These data can be used to develop different AI-based models to solve a wide range of tasks, from quality control-related problems to those concerning predictive maintenance. In fact, by extracting and analyzing the data from all the sensors, Industrial Internet of Things uses ML to help companies identify various issues and difficulties, which reduces production costs and time. It offers significant advantages for improving efficiency, equipment malfunction prediction, and quality control [8].

Abbreviations: IoT, Internet-of-Things; AI, Artificial Intelligence; ML, Machine Learning; DL, Deep Learning; SM, Smart Manufacturing; SLR, Systematic Literature Review; RL, Reinforcement Learning; UL, Unsupervised Learning; SL, Supervised Learning; LSTM, Long Short Term Memory; RF, Random Forest; KNN, K-nearest neighbors; XGBoost, Extreme Gradient Boosting; DT, Decision Tree; SVM, Support Vector Machine; PCA, Principal Component Analysis; MLP, Multilayer Perception; LR, Logistic Regression; RUL, Remaining Useful Life; WoE, Weight of Evidence; SHAPE, SHapley Additive exPlanation; LIME, Local Interpretable Model-Agnostic Explanations; NLP, Natural language processing.

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Despite the abundance of review-based research on IoT applications within Industry 4.0, there is a noticeable gap in the literature. This gap specifically concerns the integration of IoT and Advanced Analytics across diverse domains of manufacturing operations, such as Maintenance, Quality, and Production. Identifying this gap constitutes the inaugural, pioneering contribution of our study. Previous research offered an overview of the Industrial Internet of Things in intelligent manufacturing. However, it primarily focused on IoT applications without diving into specific operational domains [9]. Moreover, it did not provide a thorough examination of the algorithms and methodologies in use, especially lacking detailed insights into ML applications. In contrast, our article differentiates itself. It does so by meticulously mapping out algorithms and connecting them directly to specific use cases within manufacturing operations. This approach allows for a deeper and more nuanced understanding of these technologies' applications, marking a significant advancement in the field. Another study was conducted to provide an advanced overview of the Internet of Things' (IoT) analytical capabilities, exclusively focusing on the Supply Chain Management and Logistics sectors. [10]. Another study [11] provides a review of the current applications of ML and IoT in Industry 4.0 environments but the authors consider the two technologies (namely, ML and IoT) separately, dividing the collected papers into those related only to ML and those concerning IoT, without considering their intersection. However, the Industry 4.0 paradigm should not be viewed merely as a collection of disparate technologies; rather, the potential interactions and synergies among them constitute a significant part of Industry 4.0's value proposition [12]. In this sense, the interplay between the power of AI-based algorithms and the capabilities of IoT data-gathering can provide powerful support to pursue Operational Excellence in manufacturing contexts. However, much of the existing research on the impact of Industry 4.0 technologies on manufacturing operations focuses solely on individual technologies while there is a pressing need for more comprehensive studies that investigate the interactions among these technologies and their synergistic application [13,14]. Consequently, our study aims to contribute to the existing body of knowledge by being the first literature review to comprehensively examine the AI methods used in combination with IoT data-gathering in the specific domain of the manufacturing operations area. Furthermore, this paper sets out to accomplish several goals. Initially, it provides a detailed overview of the current state-of-the-art regarding integration between IoT and ML within manufacturing sectors. It then progresses to thoroughly examine the interpretability and maturity of the methodologies applied. Interpretability is defined as the ability to explain the connection between independent and dependent variables in terms understandable to humans. Our investigation offers a novel perspective by evaluating these methodologies not only for their predictive power but also for their interpretability. We delve into the deployment of interpretable ML techniques, offering a comprehensive analysis that extends beyond conventional model evaluation to include the practical application of these techniques in the manufacturing industry. Concerning this area, only a very few studies considered the interpretable machine learning aspects in the cyber manufacturing domains: [15] presents a review where this topic is examined but is limited to process industries applications. The authors of [16] offer a valuable review focused on ML interpretability in the predictive maintenance field. However, this review is limited to this specific maintenance field. Similarly, [17] offers an insightful overview of explainable artificial intelligence in manufacturing, presenting different applications and use cases, but they do not focus on the analysis of articles derived from a Systematic Literature Review (SLR).

Within this context, we introduce our first research question (RQ) and the related sub-questions:

RQ1: What is the state-of-the-art of the joint application of IoT and Advanced Analytics methods in the manufacturing operations areas?

RQ1.a: Which are the most used techniques?

RQ1.b: Which are the most investigated operations areas?

RQ1.c: Which are the most common applications in terms of manufacturing-related tasks?

ML and DL algorithms can be promising tools to deal with the massive amount of data collected in manufacturing contexts, leading to useful predictions and results that can provide a tangible competitive advantage for companies. However, to get the most from ML and DL algorithms, a lot of data is needed, increasing the algorithms' complexity. As their complexity rises, ML models (and DL models) become harder to understand and are frequently referred to as black-box models [18], because of these models' lack of ability to tell users about the process being investigated [19].

The lack of interpretability of most ML and DL applications is one of the key barriers to their adoption in real industrial environments [20], leading to reduced trust in ML and DL predictions [21]. The capacity to comprehend the machine-learned response function's decision-making rules and, ideally, describe the link between the independent (input) and dependent (target) variables in a way that is understandable to humans is known as interpretability [22]. To maximize the value of the data coming from IoT sensors, not only the algorithms' predictive power should be considered but it is crucial to go beyond their "black box" nature by emphasizing their interpretability dimension. In this way, a whole understanding of the processes could be obtained thereby laying the foundation to pursue Operational Excellence initiatives. Indeed, Industry 4.0 has driven a quest for more efficient production methods and organizations are refining methods and quality tools to boost efficiency and productivity. This emphasis results in the development of Operational Excellence plans, aiming for continuous improvement in processes, products, and services [23]. By validating prediction models through expert knowledge comparison, interpretable ML offers possible insights into the decision-making process. For instance, it can lower mistakes in determining potential reasons for a machine's shorter useful life [24]. To maximize the value of the data coming from IoT sensors, it is crucial to not consider only the algorithms' predictive power, but also go beyond their "black box" nature, to emphasize their interpretability and dimensions. In SM scenarios, interpretability is essential to increase confidence and automatize continuous improvement procedures such as Root Cause Analysis procedures [20], which allows for not only preventing undesired problems but also removing their main origins, thereby hampering their recurrence [25].

For instance, the most effective ML- and DL-based anomaly detection methods for analyzing sensor streams tend to be black-box, lacking interpretability despite their high performance and expressiveness [26].

Despite ML and DL algorithms have been recognized as valuable strategies for managing vast data volumes in manufacturing companies and for uncovering causal mechanisms leading from a favorable state to an undesirable one [25], no previous studies have analyzed the interpretability implications of IoT data usage in the manufacturing operations area. The extant literature in this domain is mostly limited to the development of ML and DL predictive models, without focusing on the possible extraction of relevant knowledge that could be used as a support tool during decision-making processes, enabling the achievement of continuous improvement strategies. Engineers dedicate their careers to deciphering problems and challenges that arise with black-box algorithms in industrial processes, while the use of models leading to a proper system understanding could enhance problem-solving effectiveness [15]. However, no specific studies provide reviews concerning the state-of-the-art of interpretability implications of the existing literature on the IoT-ML integration in the manufacturing sector. The second part of this work aims to fill this gap. Indeed, in order to identify possible solutions and methodologies aimed to implement data enhancement strategies through an interpretability increase is important to first map the interpretability levels of the ML and DL models currently in use in the manufacturing sector. While limiting ML and DL models to predictive purposes aids in issue anticipation, it falls short of identifying the actual causes of inefficiencies, potentially allowing inefficiencies to recur. On the contrary, links between inefficiencies and their causes should be investigated and interpreted, laying the foundation for Operational Excellence initiatives. For instance, in maintenance operations, the emphasis should extend beyond predicting machine failures, comprehending why failures occur and proactively eliminating the causes of future incidents. Hence, after addressing RQ 1, this study aims to answer the following additional RQ:

RQ2: What are the interpretability implications of the joint application of IoT and Advanced Analytics techniques in the manufacturing operations areas?

The remainder of the present article is organized as follows. In Section 2 we discuss the methodology adopted in this study. Section 3 presents and discusses the achieved results. Finally, Section 4 provides a summary of the findings, some conclusions, and directions for future studies.

Materials and methods

This work follows the systematic literature review methodology (SLR) outlined by [27], which is based on three steps consisting of planning the review, carrying out the review, and reporting the results. A SLR expands the body of knowledge by concluding a range of research in a repeatable, transparent, and inclusive manner [28].

In this paper, the review was developed by consulting the Scopus database. Aiming to restrain the search to the papers dealing with integrated applications of IoT and Advanced Analytics in manufacturing operations, the employed search string is as follows:

TITLE-ABS-KEY ((IoT OR "Internet of Things" OR "Internet-of-Things") AND ("machine learning" OR "data science" OR analytics OR BDA OR "Big Data Analytics" OR "cloud computing" OR "deep learning" OR "Computer Vision") AND (manufactur*) AND (operations OR quality OR maintenance OR production OR inventor*)) AND PUBYEAR > 2010 AND (LIMIT-TO (SUBJAREA, "ENGI") OR LIMIT-TO (SUBJAREA, "DECI") OR LIMIT-TO (SUBJAREA, "BUSI")) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English")).

Four semantic areas were defined: the first one concerning IoT, the second one contained words related to Advanced Analytics, the third one was based on the delimitation of the research on the manufacturing domain, and the last one contained terms related to operations management areas. Since Production and Planning control activities are developed based also on inventory holding [29] and inventory management is considered an area of production control [28], the term “inventory” has been inserted in the search query for completeness purposes. The search was restricted to the title, abstract and keywords of publications and the query returned 464 papers. Data was downloaded on 24–10-2023. Two duplicates were identified and removed and 350 papers were removed after the title and abstract inspection. During this phase, only works with an informative abstract were considered. Most of the discarded studies were not related to any of the manufacturing operations areas. For instance, we eliminated works that only mentioned manufacturing in the title or the abstract or works dealing with other domains (i.e., Logistics). Then, 114 papers were kept for full-text eligibility. During this stage, each paper was subjected to a thorough evaluation of the text using the following inclusion and criteria:

- C1: Studies not specifically related to the joint applications of IoT and Advanced Analytics but dealing with only one of them were excluded.
- C2: Studies not clear in terms of manufacturing applications were excluded.
- C3: Studies not clear in terms of which data or ML/DL techniques were used were excluded.
- C4: Studies whose full text was unavailable for consultation were excluded.

In the end, 42 papers were included in the final review. Fig. 1 summarizes the results of the SLR.

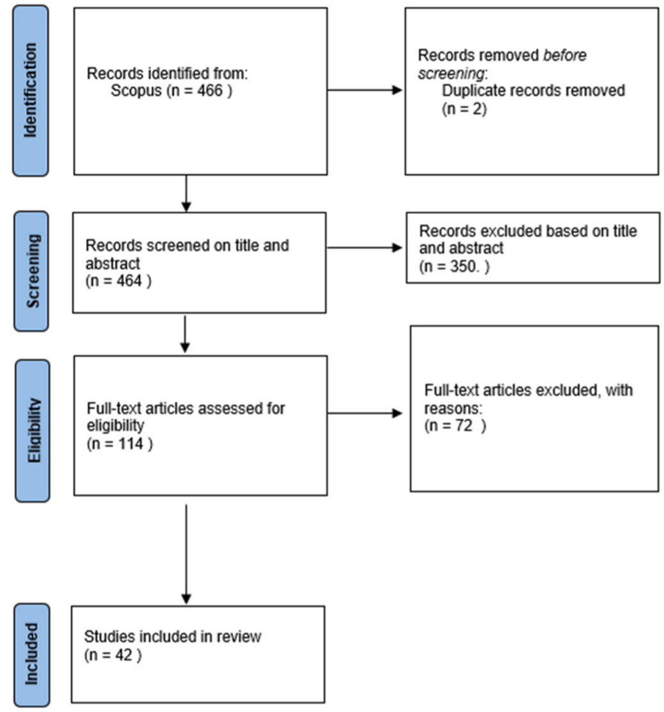

Fig. 1. PRISMA diagram.

Results

Answer to RQ1: state-of-the-art of integrated IoT and ML/DL applications in the manufacturing operations domain

To answer RQ1, all papers were carefully read and classified in terms of ML/DL techniques adopted, their operations’ domain, and the specific application described in the paper.

Three steps made up the initial classification to answer RQ1.a. First, the articles were categorized based on the ML/DL algorithms that were adopted, which included Reinforcement Learning (RL), Supervised Learning (SL), and Unsupervised Learning (UL). Hybrid categories were considered when various algorithms were studied. Then, a second categorization was done according to the ML/DL task described in the study (i.e. classification, regression). Finally, a third clusterization was performed considering the 10 most adopted algorithms. Fig. 2 shows the papers’ distribution across the ML areas, highlighting that most of the articles (23 out of 42) are concerned with SL applications while a pure UL-based approach was adopted in only 6 works. UL is used when there

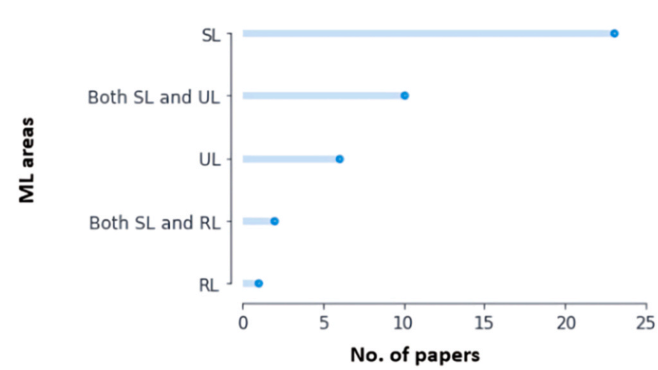

Fig. 2. Distribution of the papers across the different areas of ML, considering SL, UL, RL methodologies and their combinations.

is no target variable in the dataset and just training samples are present. Whereas if the dataset includes training samples with the target variables, SL is usually employed [30] and effectively many of the 42 considered studies use labelled data.

In the context of manufacturing applications, SL techniques are predominantly utilized because of the data-rich but knowledge-sparse nature of the tasks [31]. Nevertheless, certain facets of UL could prove advantageous in manufacturing applications: for instance, unsupervised methods are actively employed to detect anomalies in manufacturing data [31]. In RL the learning system, often called the agent, is required to independently determine the most effective sequence of actions to reach its objective by engaging with the environment [32]. Only 1 paper among those analyzed applied an RL technique.

Among the considered studies, a consistent portion described mixed different ML areas: 10 out of the 42 papers adopted combined SL-UL applications and 2 of them adopted both SL and RL-based methodologies. The increasing prevalence of unlabeled data in manufacturing is highlighting the growing significance of employing hybrid approaches that combine the strengths of both SL and UL techniques, aiming to harness the advantages of each [31].

Fig. 3 illustrates the article distribution across the ML tasks. As many of the studies consider SL applications, we can see that the most employed tasks are regression and classification tasks. They represent versatile techniques that can be applied to solving different kinds of problems, ranging from predictive maintenance-related tasks to quality control applications, as will be discussed more in detail later in this section. However, as seen in Fig. 2., several studies considered combined SL and UL algorithms, thereby dealing with combined ML/DL tasks. Indeed, 13 studies described mixed ML tasks. In most cases, where a combined UL-SL approach is proposed, a UL technique is applied to the dataset before the application of an SL-based algorithm. In a study [33] several UL-based methods (Clustering, PCA, Autoencoder) are applied to the dataset before using the chosen SL algorithms. Other studies adopt a UL-based feature extraction methods before the application of an SL model [34-38]. Whereas in other papers [39-41] dimensionality reduction techniques are employed before using an SL method. Among the papers proposing a mixed SL-RL approach, 1 study [39] proposes an RL approach after the application of an SL algorithm while another work [42] describes a simultaneous application of a regression task and an RL-based task to build a unique model.

Fig. 4 illustrates the distribution of papers based on the top 10 adopted algorithms considering the algorithms appearing in a minimum of 2 papers. Notably, among DL models, Long Short-Term Memory (LSTM) emerged as the most frequently employed technique. A majority of studies employing LSTM focused on predicting the Remaining Useful Life (RUL) of assets, aligning with findings by [22], who identified Recurrent Neural Networks (RNNs) and LSTM as the predominant DL methodologies for RUL predictions.

Within the category of non-DL methodologies, the Random Forest (RF) algorithm stands out as the most frequently employed. Renowned for its versatility, RF excels in both regression and classification tasks, rendering it a versatile tool suitable for addressing a diverse array of challenges. Moreover, it effectively mitigates the tendency of Decision Trees (DTs) to overfit data [31]. These findings are consistent with the conclusions reached by [43], identifying RF and DTs as the most widely utilized data science techniques within the Industry 4.0 domain. They are both SL-based models and this outcome aligns with the findings presented in the study of [44], where SL methodologies are recognized as the most employed ML techniques within the engineering and manufacturing domain.

In answering RQ1.b and RQ1.c, an additional classification was undertaken to cluster various operational domains and their corresponding applications, respectively. Assessing the paper content, articles were divided based on three distinct operation areas and their related applications, as shown in Fig. 5:

The Maintenance area is the most covered domain, and it includes 24 papers (out of 42), of which 20 deal with Predictive Maintenance, 3 cover the Condition Monitoring topic, and only 1 is related to Prognostics and Health Management applications. Notably, most of the works cover Predictive Maintenance applications. Indeed, given the escalating demand to reduce downtime and economic losses, Predictive Maintenance is considered a prominent strategy for predicting anomalies in manufacturing systems [35] and ML techniques have become a promising tool in Predictive Maintenance applications for effective manufacturing in Industry 4.0, attracting considerable attention from authors and researchers in recent years [45].

Quality is the second-most covered manufacturing operations area, including 11 papers of which 8 deal with Quality Control and 3 with Quality Assurance. Particularly, research focused on applying ML techniques to Quality Control has been a prominent subject of investigation in recent years [46]. At the same time, IoT is considered pivotal for Quality Control, utilizing sensors for real-time defect detection and prompt issue rectification to prevent defective products from entering the market. The sensors monitor products throughout manufacturing, identifying defects and ensuring adherence to quality standards [47].

Finally, Production is the most under-explored manufacturing operations area with only 6 papers, of which 4 deal with Planning and Control, 1 with Idle time reduction, and 1 with Process parameter optimization. These last results align with the findings of the study proposed by [46], where a review concerning ML applied in production planning and control is presented. Here, the authors highlight that 75% of the potential research domains within the ML and Production Planning and Control intersection are either minimally explored or not addressed entirely. The authors stress that this lack of research should be attributed to the complexity involved in utilizing IoT technologies for data collection and the challenge of updating the ML model to align with changes in the manufacturing system.

Table 1 summarizes the findings described in this section.

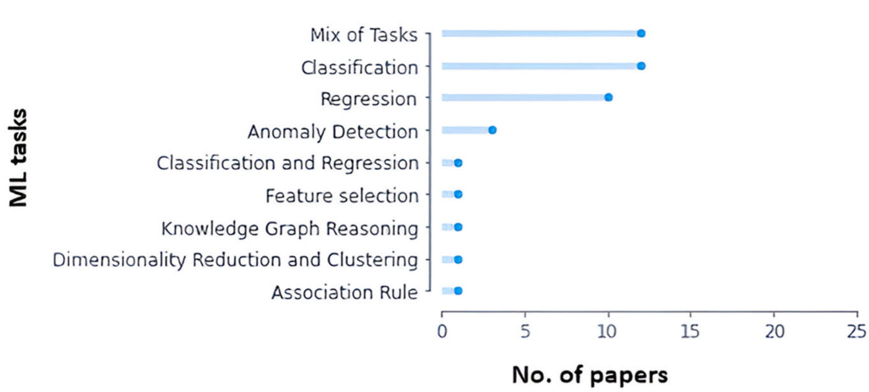

Fig. 3. Distribution of papers per ML task.

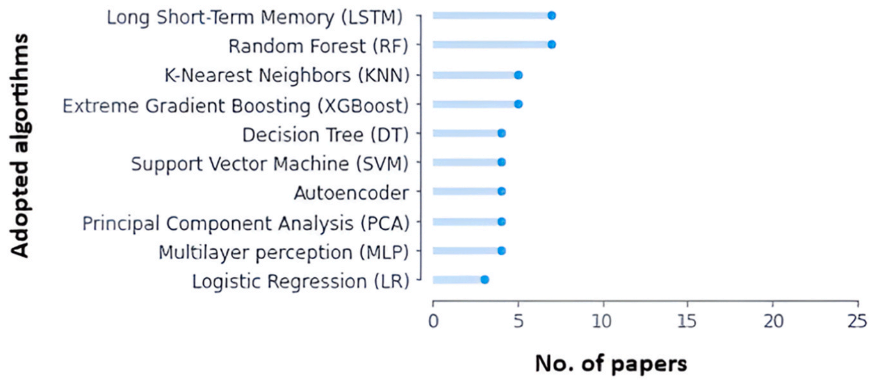

Fig. 4. Distribution of the papers per adopted algorithm considering the top 10 most used ML algorithms.

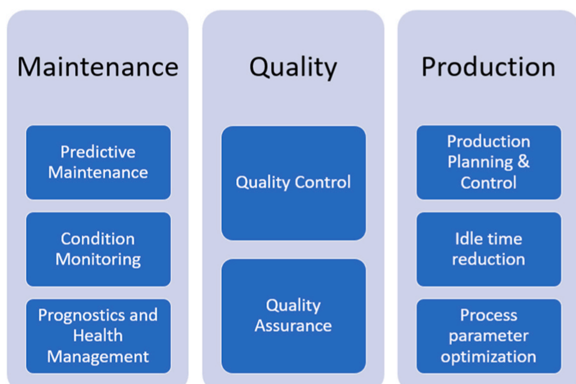

Fig. 5. Classification of the identified manufacturing operations areas.

Answer to RQ2: interpretability implications of the existing literature

To answer RQ2, a first classification of the selected papers was made by adopting the taxonomy proposed by [79], illustrated in Fig. 5.

Interpretable ML methods used before model training are known as ante-hoc techniques, whereas those applied after training are categorized as post-hoc techniques [16]. Ante-hoc techniques refer to the usage of algorithms known as intrinsically interpretable models. Common examples within this category include models such as linear/logistic regression or decision rules [80]. Intrinsically interpretable models refer to algorithms that humans can directly comprehend. For instance, by examining the structure of a DT, it is possible to visually deduce the most crucial input features affecting the final prediction [81]. Conversely, post-hoc methods comprise those ML and DL algorithms employed on black-box models after training. These methods interpret and elucidate the importance of particular input features on the output, generating interpretations by scrutinizing the relationship between input features and predictions [79].

Regarding the interpretability scope, the term global interpretability refers to understanding how a model works from an overall point of view, while local interpretability aims to provide specific explanations concerning each individual prediction, considering one single given output.

Finally, model-specific methods are limited to that model or a specific class of models. In contrast, model-agnostic methods can be utilized for any model, as long as the features and model outputs align with the chosen explanation approach [16].

Given the above definitions, the 42 selected papers were reviewed and classified according to the application stages of interpretable ML techniques (i.e., differentiating between ante-hoc and post-hoc approaches), then identifying their interpretability scope (i.e., global or local), and the model dependency implications (i.e., model-specific or model-agnostic methods). It was observed that only 7 out of the 42 papers adopted at least one intrinsically (ante-hoc) interpretable model. More specifically the adopted approaches were the DT, Linear Regression, Logistic Regression and KNN. Concerning the usage of post-hoc techniques, the most preferred approach was the feature importance analysis, distinguishing it between model-agnostic and model-specific methods. Regarding model-agnostic methods, in the study proposed by [76], the concept of interpretability using feature importance is highly stressed, through the proposal of a new interpretable ML approach called "Balanced K-Star" for Predictive Maintenance. This method is built upon the K-Star classification algorithm. Here, the chi-square method was employed on the predictive maintenance dataset to identify the key factors influencing the occurrence of machine failures. Indeed, in this work a logical failure tree is employed by looking at the variables leading to specific failure types, enhancing the transparency of the ML prediction process and highlighting the impacting features for each type of machine failure. In the work by [50], the feature importance in the proposed RF and XGboost models is performed through the Weight of evidence (WoE) approach, a probabilistic method for variable importance analysis. In the work proposed by [37], the interpretability of the developed RF model was measured according to the feature permutation importance, as in the study proposed by [38] and the one by [40], which represents a model-specific variable importance based on an RF algorithm. Fig. 6.

As already mentioned, over the past ten years, significant advancements have been achieved by ML and DL algorithms in various tasks but due to a lack of a comprehensive grasp of their internal mechanism, they are frequently treated as enigmatic "black boxes" [82]. Out of the examined papers focusing on those utilizing DL-based models, only 2 try to make clear the internal structure of the proposed model and the reasons behind the obtained predictions. One such effort is found in the study by [52], where the authors employ visual presentations and comparisons among different configuration alternatives to identify crucial features. They characterize this process as an attempt to demystify the black-box nature of the proposed neural network model. They emphasize that through this approach, the internal structure of the neural network becomes explicitly interpretable, empowering users to pinpoint the origin of misclassifications. However, the study lacks specificity regarding the adopted methodology and does not place substantial focus on this step. The second attempt in this sense is found in the work by [48], where a Deep Belief Learning based DL (DBL-DL model) is used to explain the relationship between the sensor signals and the defect types.

Table 2 provides a summary of the findings from this section, revealing that only a few studies explicitly address potential implications for interpretability, indicating a notable research gap. The methods primarily employed for enhancing interpretability are ante-hoc techniques, as evidenced by the studies that offer the greatest potential for interpretability insights. Within the realm of post-hoc techniques,

Table 1
Summary of the findings related to RQ1.

References	Operations area	ML area	ML task	Application
[48]	Quality	SL	Classification	Quality Control
[49]	Maintenance	**SL**	Classification	Predictive Maintenance
[50]	Quality	SL	Classification	Quality Control
[51]	Maintenance	UL	Anomaly detection	Predictive Maintenance
[52]	Maintenance	SL	Regression	Predictive Maintenance
[41]	Production	Both SL and UL	Mix of tasks	Production planning and control
[53]	Production	Both SL and UL	Mix of tasks	Production planning and control
[54]	Maintenance	UL	Dimensionality Reduction and Clustering	Predictive Maintenance
[34]	Production	Both SL and UL	Mix of tasks	Production planning and control
[55]	Maintenance	SL	Classification	Predictive Maintenance
[56]	Maintenance	SL	Classification	Predictive Maintenance
[38]	Maintenance	Both SL and UL	Mix of tasks	Condition monitoring
[57]	Quality	SL	Classification	Quality Assurance
[58]	Maintenance	UL	Feature selection	Predictive Maintenance
[59]	Maintenance	SL	Regression	Condition monitoring
[60]	Maintenance	SL	Classification	Condition monitoring
[40]	Maintenance	Both SL and UL	Mix of tasks	Predictive Maintenance
[61]	Maintenance	SL	Classification and regression	Predictive maintenance
[62]	Maintenance	SL	Regression	Prognostics and Health Management
[35]	Maintenance	Both SL and UL	Mix of tasks	Predictive Maintenance
[33]	Maintenance	Both SL and UL	Mix of tasks	Predictive maintenance
[63]	Quality	SL	Classification	Quality Control
[64]	Maintenance	Both SL and RL	Mix of tasks	Predictive Maintenance
[65]	Production	SL	Regression	Process parameter optimization
[66]	Quality+Maintenance	SL	Regression	Quality Management + Predictive Maintenance
[67]	Maintenance	SL	Regression	Predictive Maintenance

Table 1 (*continued*)

References	Operations area	ML area	ML task	Application
[42]	Production	Both SL and RL	Mix of tasks	Production planning and control
[68]	Maintenance	SL	Classification	Predictive Maintenance
[69]	Maintenance	UL	Anomaly detection	
[70]	Quality	UL	Anomaly detection	Quality Control
[37]	Maintenance	Both SL and UL	Mix of tasks	Predictive Maintenance
[39]	Quality	Both SL and UL	Mix of tasks	Quality Control
[71]	Maintenance	SL	Regression	Predictive Maintenance
[72]	Quality	UL	Association Rule	Quality Assurance
[73]	Quality	SL	Classification	Quality Control
[74]	Production	SL	Classification	Idle time reduction
[36]	Maintenance	Both SL and UL	Mix of tasks	Predictive Maintenance
[75]	Quality	SL	Regression	Quality Control
[76]	Maintenance	SL	Classification	Predictive Maintenance
[77]	Quality	RL	Knowledge Graph Reasoning	Quality Control
[78]	Maintenance	SL	Regression	Predictive Maintenance
[21]	Quality	SL	Regression	Quality Assurance

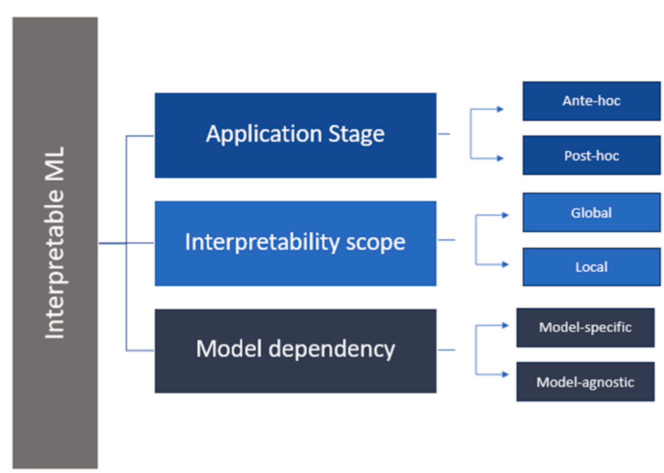

Fig. 6. Adopted interpretability taxonomy.

feature importance stands out as the most commonly used traditional method. Additionally, it is observed that the remaining studies, deemed relevant for deriving interpretability insights, rely on unconventional methods. For example, visualization-based approaches suggest a non-standard strategy towards tackling interpretability issues.

In line with previous findings, if the literature concerning the interpretability of ML algorithms is limited, even scarcer is the

Table 2
Summary of the findings related to RQ2.

References	ML area	Potential Interpretability Insights	Approach	Application
[48]	SL	✓	DBL-DL model	Quality Control
[49]	SL	✓	Logistic Regression	Predictive Maintenance
[50]	SL	✓	Feature importance	Quality Control
[51]	UL			Predictive Maintenance
[52]	SL	✓	Visualization	Predictive Maintenance
[41]	Both SL and UL			Production planning and control
[53]	Both SL and UL			Production planning and control
[54]	UL			Predictive Maintenance
[34]	Both SL and UL			Production planning and control
[55]	SL	✓	Decision Tree, KNN	Predictive Maintenance
[56]	SL			Predictive Maintenance
[38]	Both SL and UL	✓	Feature importance	Condition monitoring
[57]	SL	✓	KNN	Quality Assurance
[58]	UL			Predictive Maintenance
[59]	SL			Condition monitoring
[60]	SL			Condition monitoring
[40]	Both SL and UL	✓	Feature importance	Predictive Maintenance
[61]	SL			Predictive maintenance
[62]	SL			Prognostics and Health Management
[35]	Both SL and UL			Predictive Maintenance
[33]	Both SL and UL			Predictive maintenance
[63]	SL	✓	Logistic Regression, Decision Tree	Quality Control
[64]	Both SL and RL			Predictive Maintenance
[65]	SL			Process parameter optimization
[66]	SL	✓	Linear Regression	Quality Management + Predictive Maintenance
[67]	SL			Predictive Maintenance
[42]	Both SL and RL			Production planning and control
[68]	SL			Predictive Maintenance
[69]	UL			
[70]	UL			Quality Control
[37]	Both SL and UL	✓	Feature importance	Predictive Maintenance
[39]	Both SL and UL			Quality Control
[71]	SL			Predictive Maintenance
[72]	UL			Quality Assurance
[73]	SL			Quality Control
[74]	SL			Idle time reduction
[36]	Both SL and UL			Predictive Maintenance
[75]	SL	✓	Decision Tree	Quality Control
[76]	SL	✓	Balanced K-Star	Predictive Maintenance
[77]	RL			Quality Control
[78]	SL			Predictive Maintenance
[21]	SL			Quality Assurance

analogous literature in the context of DL algorithms. As observed, there is a lack of research in making the DL-based model transparent and clearly interpretable. The lack of transparency in AI solutions, particularly in the black-box algorithms of DL methods, can limit the transferability of approaches to changes in domains, diminishing the fairness of decision-making and in the manufacturing domain, transferability is a very relevant concept [83]. Indeed, within the manufacturing sector, it is essential to ensure the effective application or reproduction of knowledge in various scenarios or situations. This entails successfully adapting and implementing best practices and techniques from one context to another. However, different powerful models could be adopted to open black-box models, providing more accurate explanations of the outputs, such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) which stand out as widely utilized approaches in interpreting ML models in a post-hoc way. Besides SHAP and LIME, other methods which can specifically support interpreting DL algorithms have been presented in the comprehensive overview offered by [84]. These additional methods are decompositions of DL models into decision trees (e.g., the DeepRED and ANN-DT methods) and methods based on the salience map approach (e.g. DeepLIFT).

The primary objective of these methods is to offer clarity on the decision-making mechanisms of a model, enhancing the interpretability of its predictions for human comprehension. These methods have been widely applied in different industries but, from the results of this review, they have been under-explored in the manufacturing sector although they are considered powerful methods capable of handling data to assist practitioners in the decision-making process through an enhancement of the comprehension of AI models' output [85].

Conclusions

This state-of-the-art analysis studied 42 research articles selected through the process of an SLR. The articles included in the final review were carefully examined focusing on mapping the predominant ML and DL techniques adopted, their main applications, and the key areas of manufacturing operations in which they were applied. Then this work aimed to provide an analysis concerning the interpretability implications of the proposed ML and DL algorithms. Integrating IoT data-gathering capabilities with ML and DL algorithms can represent a powerful synergy in improving manufacturing operations, thus enabling Operational Excellence The review results show that ML and DL algorithms are widely applied in these areas. As seen in the preceding sections, there are different contributions to the existing literature looking at the function of integrated IoT and ML-DL solutions and their uses in the examined manufacturing operations areas.

In terms of prevailing ML and DL algorithms, most of the scrutinized studies opt for SL methods, with UL approaches following closely behind. Conversely, only a small proportion of works make use of RL algorithms. When considering the most frequently applied models, a specific variant of RNNs, namely LSTM, and the RF algorithms are identified as the most used techniques. Regarding the most extensively explored applications, the results suggest a pronounced focus within the scientific literature on addressing tasks related to Maintenance. Predictive maintenance stands out as the most thoroughly investigated manufacturing operations domain while only a few studies are related to the Production area, suggesting further research in this domain.

Findings related to the implications of interpretability indicate that the existing literature in this field has given little attention to this topic. Specifically, the majority of examined papers do not explicitly incorporate the concept of interpretability in their research. Among the 42 selected studies, 7 are categorized as interpretable and they primarily rely on intrinsically (ante-hoc) interpretable models. Notably, even though many works utilize DL algorithms, they often lack post-hoc explanations for their models. Consequently, the results of this second investigation suggest some challenges opening further research in this area. First, as observed, most of the papers do not deal with the interpretability concept within their studies. Indeed, most of the works are highly focused on the predictive power of the developed models, without considering the reasons leading to the obtained output. AI methodologies are often regarded as black boxes, with little or no effort made to clarify the outcomes. As a result, there is skepticism surrounding AI results in the manufacturing sector since is crucial to provide an explanation of why the solution works and interpret the results for widespread adoption in manufacturing [86]. Based on this, further research should focus on incorporating this concept in their research, to derive further implications, for instance concerning explanations regarding the reasons for a failure and making more informed decisions. As mentioned in the previous section, the LSTM model is the most used algorithm in the field of RUL prediction. However, none of the studies employed any specific post-hoc technique, which could be essential to fully understand the reasons behind machine degradation. Accordingly, the use of intrinsically interpretable models and, particularly, of post-hoc techniques should be solicited as possible approaches to make the existing ML models leveraging Industrial IoT data more interpretable, consequently transforming them into suitable tools for implementing continuous improvement strategies. Consequently, filling this gap and further investigating the use of interpretable ML in the manufacturing sector would be beneficial to enhance transparency, contributing to improved decision-making and the achievement of Operational Excellence. Indeed, if operators and engineers can interpret ML and DL model outputs, these models can provide valuable insights for refining and optimizing parameters regarding the main operations areas, through a continuous improvement process. For instance, concerning the Quality domain, interpretable models could help in the assessment of the main factors influencing product quality to then implement targeted improvements. At the same time, interpretable models can help maintenance teams understand the factors that mostly contribute to equipment failures. They could be supported in making informed decisions about when and how to schedule maintenance activities, to avoid unplanned repairs and consequently reduce costs. In particular, the integration of post-hoc methodologies opens the possibility of extensively utilizing in an interpretable way more advanced models, such as those based on DL algorithms that often yield more accurate predictions. Indeed, the application of post-hoc techniques to these models enables the opportunity to extract valuable information about the outcomes they produce. At the same time, further research in this domain would be important also from a theoretical perspective since the models described in the existing literature could be opened through the exploitation of methodologies that have not been exploited yet in this domain, expanding the existing body of knowledge. New theoretical implications could be derived by opening and interpreting the models employed in previous works. For instance, the trade-off between model interpretability and accuracy could be explored, leading to the development of models achieving an optimal balance between transparency and predictive power. Consequently, this could also set the foundation for the definition of interpretability metrics in the manufacturing sector, allowing the reproducibility and transferability of the results in different scenarios.

Then, a lack of use of local interpretability methods has been observed since none of the analyzed studies employed any local post-hoc techniques after the model development. Utilizing local interpretability methods could yield more precise explanations, highlighting the factors contributing to particular events. This approach could assist in highlighting anomalies in specific instances of manufacturing processes, enabling operators to comprehend how certain factors influence the occurrence of specific events. For example, in the area of Maintenance, distinct parameters might lead to the failure of one machine while not affecting another, prompting further investigation into the underlying differences. At the same time, examining individual product quality could benefit from a focus on local interpretability.

Finally, integrating domain knowledge into interpretable models is key for developing suitable models that operations managers can effectively use, potentially leading to the design of tools dedicated to pursuing Operational Excellence. This need is also stressed in the work proposed by [16]. It can be done through for example the inclusion of text mining and Natural Language Processing (NLP) algorithms in the models' development, to integrate external information coming from text-based data or recordings.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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