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TỔNG QUAN ỨNG DỤNG MÁY HỌC TRONG SẢN XUẤT: TỪ CHUYÊN MÔN HÓA ĐẾN HỌC CHUYỂN GIAO

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TỪ KHÓA

Học máy;
Chức năng sản xuất;
Trí tuệ nhân tạo;
Sản xuất thông minh.

TÓM TẮT

Sự chuyển đổi của các hệ thống sản xuất theo các mô hình Công nghiệp 4.0 và 5.0 đã thúc đẩy nhanh chóng việc áp dụng Máy học (Machine Learning - ML) trong lĩnh vực này. Với sự gia tăng nhanh chóng của các nghiên cứu sử dụng ML để nâng cao các chức năng sản xuất, bài báo này nhằm cung cấp một cái nhìn toàn diện và cập nhật về các ứng dụng đó. Tổng cộng 114 bài báo khoa học đã được thu thập, phân tích và phân loại dựa trên các phương pháp giám sát, thuật toán ML và các lĩnh vực ứng dụng. Nghiên cứu làm nổi bật những lợi ích của ML trong sản xuất, đồng thời xác định các hướng nghiên cứu tiềm năng cho tương lai. Đáng chú ý, bài báo nhấn mạnh rằng xu hướng hiện tại của các ứng dụng có tính chuyên môn hóa cao có thể được giải quyết bằng cách thúc đẩy áp dụng các phương pháp học chuyển giao (transfer learning) trong lĩnh vực sản xuất.

OVERVIEW OF MACHINE LEARNING APPLICATIONS IN MANUFACTURING: FROM SPECIALIZATION TO TRANSFER LEARNING

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ABSTRACT

The shift of manufacturing systems toward the paradigms of Industry 4.0 and 5.0 has significantly boosted the integration of Machine Learning (ML) technologies in this field. With the rapid growth of research leveraging ML to enhance manufacturing functions, this review aims to provide a thorough and up-to-date overview of these applications. A total of 114 journal articles were collected, analyzed, and categorized based on supervision approaches, ML algorithms, and application domains. The study highlights the benefits of ML in manufacturing, alongside identifying potential avenues for future research. Notably, the paper highlights that the prevalent focus on highly specialized applications in manufacturing could be mitigated by encouraging the implementation of transfer learning within the industry.

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1. INTRODUCTION

The evolution of manufacturing systems toward smarter, more digital, and autonomous operations has progressed swiftly. According to Kusiak's concept of smart manufacturing [1], this transformation is accompanied by significant challenges, including greater flexibility, adaptability, and resilience. For manufacturing companies to move in this direction, implementing technologies such as computer control systems, information systems, production management software, and sensor networks is essential. However, the adoption of these technologies alone does not suffice for a manufacturing system to be deemed truly smart. To achieve intelligence, the system must be governed by advanced technologies that ensure the stability and repeatability of production processes [2].

The rapid development of Artificial Intelligence (AI), particularly in fast, accurate, and adaptive applications, has significantly reduced the number of tasks traditionally performed and controlled by humans [3]. Within the field of AI, Machine Learning (ML) has emerged as a transformative tool in the manufacturing industry. The maturity of ML systems is evident in their ability to address complex challenges, such as time-dependent dynamics [4]. Categorized into five primary types based on the training methodology: supervised learning (SL) [5], unsupervised learning (UL) [6], reinforcement learning (RL) [7], semi-supervised learning (Semi-SL) [8], and self-supervised learning (SSL) [9]. In particular, SL algorithms involve labeled data with defined inputs and outputs, while UL algorithms identify patterns without predefined outputs, utilizing clustering and association algorithms [10], [11]. RL algorithms focus on learning optimal actions in an environment to achieve specific goals [12]. Semi-SL combines SL and UL by leveraging large unlabeled datasets alongside smaller labeled ones [13].

Furthermore, ML has become a crucial asset in the manufacturing industry, offering the ability to model and predict intricate relationships between experimental and simulation data. This capability makes ML an essential tool for optimizing manufacturing processes [14], [15]. With the growing demand for greater autonomy in manufacturing systems, ML applications provide effective solutions to address challenges such as process optimization, predictive maintenance, and quality control [16].

The increasing adoption of sensor networks in manufacturing has resulted in an explosion of data generation, creating vast amounts of raw data that can be utilized to develop intelligent systems. These systems enable manufacturers to analyze data in real time, enhance decision-making processes, and identify inefficiencies [17]. Moreover, ML is capable of addressing complex and dynamic problems that were traditionally beyond the scope of conventional manufacturing techniques [18].

As a result, ML has the potential to revolutionize manufacturing systems by facilitating greater intelligence and autonomy, driving innovation, and enabling smarter, data-driven operations. The integration of ML in manufacturing is therefore becoming a critical step in advancing the transition toward Industry 4.0 and beyond [19], [20].

This review advances the understanding of ML applications in manufacturing by providing a comprehensive classification of ML support based on key functions, input and output data, supervision approaches, and application domains. Building on frameworks proposed in [21], and [22], the review outlines five key functions: material selection, production planning, process selection, monitoring, and quality control. This classification highlights how ML drives innovation, enhances decision-making, and improves efficiency and product quality across various manufacturing processes.

This paper aims to showcase the potential of ML by examining its applications in the manufacturing sector. It categorizes these applications systematically, shedding light on their use and significance. Additionally, the paper emphasizes the primary drivers and expected advantages of adopting ML, providing a deeper understanding of its role in revolutionizing manufacturing processes.

2. MATERIALS AND METHODOLOGY

This study uses a 'mapping review' approach, beginning with a Scopus literature search in 2023. The search targeted the fields of "Title," "Abstract," and "Keywords" using a combination of search terms linked through an AND operator. These terms were divided into two distinct groups:

1. ML Presence: Terms related to ML connected by an OR operator, including variations such as "machine learning" and "supervised learning."

2. Manufacturing Field: Terms representing the manufacturing domain using the wildcard string "manufactur *."

Scopus results were filtered by language English, journal articles, and subject area Engineering or Material Science. This systematic approach ensured the inclusion of high-quality, relevant studies for the review. The search conducted through the Scopus database and subsequent filtering initially identified a total of 3,887 articles. Abstracts were reviewed to ensure a clear connection between learning and manufacturing concepts. This screening narrowed the selection to 155 articles. Following this, the full texts of the available articles were examined, and only those that clearly stated in their introduction a focus on using ML to support manufacturing were included. As a result, 114 articles were ultimately chosen for the scope of this review. The entire article selection process is summarized in Fig. 1.

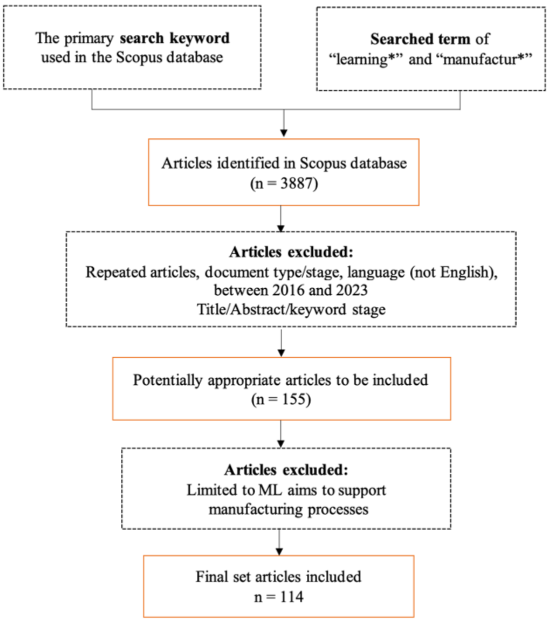

Figure 1. *PRISMA diagram for showing the article selection*

3. RESULTS AND DISCUSSION

3.1 The distribution of articles

Figure 2 illustrates the classification of journal articles from this study based on their manufacturing functions and publication years. Notably, there has been a steady rise in the number of articles published since 2017, signaling a potential turning point for the widespread adoption of machine learning (ML) systems in the manufacturing industry. This upward trend suggests that the integration of ML into manufacturing has gained momentum, and it is likely that the volume of related publications will continue to grow in the foreseeable future.

Figure 2. *Articles reviewed by manufacturing functions and publication years*.

Moreover, Fig. 2 illustrates the exponential growth in the number of publications focusing on machine learning (ML) applications in manufacturing. This upward trend suggests that the field is rapidly expanding, with many new applications and research proposals anticipated in the coming years. However, this growth does not necessarily ensure the standardization of practices, the development of dominant systems, or seamless integration between various algorithms, as discussed earlier.

Currently, it remains challenging to gauge the true impact of ML adoption on manufacturing capabilities and efficiency. Few studies document the widespread implementation or large-scale success of specific algorithms in practice. From the authors' perspective, one of the key barriers to accelerating the adoption of ML in manufacturing is the significant challenge of data labeling, which remains a critical hurdle to overcome.

3.2 Analysis of Keyword Co-occurrence

To analyze the selected set of articlesThe VOSviewer tool was used to generate and visualize bibliometric networks. Figure 3 displays keyword co-occurrence, highlighting key themes in the article set. Node size reflects the number of articles linked to a keyword while connecting lines indicate relationships between terms.

Notably, The largest nodes represent algorithms, statistical functions, and learning typologies, rather than manufacturing operations, indicating a technology-push dynamic dominated by computer science. This is interpreted as evidence that ML is primarily driven by advancements in computational methods, researchers primarily focus on algorithm development for manufacturing contexts, while manufacturing scholars may more selectively explore ML as a solution for specific, well-defined problems.

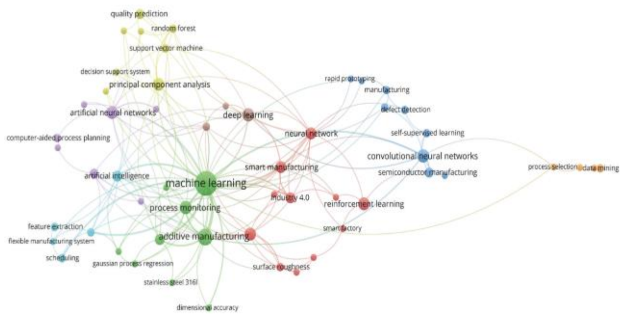

Figure 3. *Analysis of Keyword Co-occurrence*

3.3 Classification of articles

Figure 4 categorizes the articles reviewed in terms of ML algorithms and their application to manufacturing functions. Notably, the majority of ML algorithms supporting manufacturing rely on SL, which requires labeled data - a significant limitation for industrial implementation. This challenge is further explored in the section titled "Limitations of Using Machine Learning in Manufacturing."

Several studies in [23] and [24] have employed multiple ML algorithms to address the same problem, aiming to identify the most effective approach. These comparative analyses contribute to the evaluation and refinement of ML methods, helping to determine optimal solutions for specific manufacturing challenges.

Figure 4 highlights that, consistent with prior reviews [25], [26] and studies from engineering and related fields [27], ANN-based algorithms are the most commonly utilized ML techniques in the reviewed articles. This prevalence can be attributed to ANNs' ability to mimic the human brain and their versatility across various applications. The RL algorithms focus on production scheduling, while other ML methods are evenly distributed across manufacturing functions, as shown in Fig. 5.

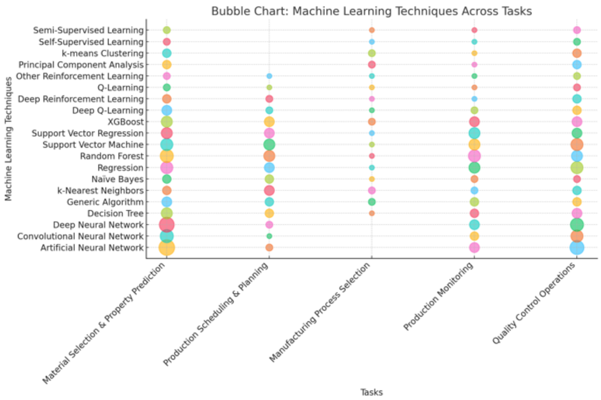

Figure 4. *Articles are categorized by ML algorithms, supervision types, and functions.*

This review highlights the dynamic and expansive research landscape of ML-supported manufacturing technologies, characterized by numerous niche applications. These applications, while diverse, share minimal overlap, showcasing the adaptability of ML methods. However, the research field appears fragmented, with limited collaborative efforts and a lack of continuity in building upon previous studies. This fragmentation can be attributed to several factors:

- **Limited Public Access to Algorithms**: Few studies have made their developed algorithms publicly accessible, restricting the opportunity for further development and collaboration.
- **Company-Specific Solutions:** Some applications address unique challenges faced by specific manufacturing companies, limiting their generalizability and hindering the full disclosure of results due to confidentiality concerns.
- **Technology-Push Dynamics:** In some cases, ML applications seem to focus on showcasing the feasibility of ML implementation rather than addressing practical manufacturing needs. This technology-driven approach prioritizes demonstration over systematic integration, reducing the potential for synergy with other proposals.

The subsequent discussions aim to identify commonalities, address gaps, and explore opportunities for the collaborative use of ML-based algorithms. The goal is to enhance the engineering dimensions of manufacturing processes, broadening their scope and impact.

3.4 Research Opportunities

The review has identified several underexplored areas that present promising research opportunities:

- **Combining Manufacturing Functions:** There is significant potential in using ML to integrate multiple manufacturing functions. For example, combining scheduling and monitoring could result in advanced production schedules that incorporate maintenance planning for machines and tools.
- **Unsupervised and Semi-Supervised Learning:** Most existing ML applications rely on supervised learning (SL), which requires labeled data. However, with the increasing availability of unlabeled data, leveraging unsupervised learning (UL) or semi-supervised learning (SSL) presents a valuable opportunity for analyzing manufacturing functions.
- **Expanding Applications in Process Selection:** While much of the research focuses on specific technologies, ML applications could be extended to assist in selecting manufacturing processes. This would include evaluating both traditional and additive manufacturing technologies to improve decision-making.
- **Comparative Evaluation of Algorithms:** Exploring different ML algorithms for the same manufacturing function could help determine the most effective solution for specific applications. Such comparative analyses, as noted by Garouani et al. in [29], can guide the optimal selection of algorithms.

4. CONCLUSION

This review offers a comprehensive analysis of 114 journal articles on ML applications in manufacturing, spanning key functions like material selection, production scheduling, process selection, monitoring, and quality control. While ML has driven notable improvements in these areas, challenges such as data processing and labeling remain significant. To address these gaps, future research should focus on developing algorithms that tackle multiple functions, leveraging transfer learning, and exploring hybrid systems that integrate supervised and unsupervised learning. Additionally, creating synthetic datasets, utilizing semi-supervised learning to overcome data labeling limitations, and applying ML to optimize hybrid manufacturing processes present valuable opportunities to further enhance ML's impact in manufacturing.

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