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Research Article

Industry 4.0- Applications of machine learning in the field of industrial engineering: Systematic review of the literature

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Abstract

The aim of this research is to determine how the implementation of machine learning has generated advantages in the field of engineering. Through a systematic review of the literature, it seeks to understand the importance of machine learning and its various applications in engineering, such as equipment maintenance, business demand forecasting, production chain optimization, customer service, and quality control. In this article, we conduct a systematic review and bibliometric analysis to explore the current state of research on machine learning and Industry 4.0 applications in the field of industrial engineering. Our goal is to identify established and emerging fields of research to guide future research. To carry out this study, we initially identified 926 scientific journal publications indexed by publishers such as Ebsco essentials, ScienceDirect, IEEEXplore, and MDPI, collected from 1 January of 2015 to June 2024. Subsequently, a group of specialists evaluated these publications, carefully selecting 88 of them that were placed in the literature review section and that were considered relevant to our analysis. In a second stage, we applied a detailed analysis using MAXQDA v.2020 software on our collected data, focusing on citation and keyword evaluation. This approach allowed us to gain a deeper understanding of trends and connections in existing research in this field.

Keywords: Machine Learning; Industry 4.0; Supply Chain; maintenance; Artificial intelligence; Deep Learning; Additive Manufacturing.

1. Introduction

Industry 4.0 has unleashed an unprecedented revolution in engineering, completely redefining the conception, design, and operation of production and manufacturing systems. In this context, machine learning, also known as machine learning (ML), emerges as an essential tool that drives efficiency, accuracy, and innovation in a wide range of engineering applications. From process optimization to predicting machine failures, the use of machine learning is transforming the way engineers approach challenges across industries, delivering smarter, more adaptive solutions.

Machine learning has emerged as a critical component in the Industry 4.0 framework, thanks to its ability to identify patterns in massive data sets and perform predictive analysis without the need for manual programming. This revolutionary approach extends from supply chain optimization to improving teaching by creating learning models. The support of researchers such as Duong et al. (2023) and Choudhary et al. (2022) shows how ML can simplify entire experimental cycles and reduce errors, thus promoting greater efficiency in industrial processes.

The intersection between engineering and machine learning technologies is reshaping the way business models are developed. Examples such as the Marketplace illustrate how better benefits can be achieved at lower cost by implementing ML-based strategies (Romero et al., 2021). In the environment of the Industrial Revolution 4.0 (I4.0), characterized by interconnection, big data, cyber-physical systems and machine learning, machine learning and the Internet of Things (IoT) emerge as crucial elements for business transformation. Sectors such as e-commerce have seen remarkable progress thanks to these technologies (Sazzadur et al., 2023; Hermann, 2015).

The technological advancements of Industry 4.0 are redefining industrial production by meeting the demands of smart technology. Early detection of critical events, such as fatigue cracks in machine components, is made possible by machine learning (Drakaki et al., 2022). This capability has positioned ML as an essential component in the digitalization of production system operations, highlighting its applicability in materials engineering and other fields (Chen et al., 2023; Amin et al., 2021). Although ML promises significant improvements, real-time fault detection remains a challenge due to the

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complexity of mechatronic control systems (Velásquez et al., 2022).

Given its dynamism, Industry 4.0 represents a new paradigm where value chains are driven by intelligent connectivity and automation. Machine learning emerges as a critical tool for improving problem environments on a large scale, thereby increasing the performance of industrial operations (Mazzei & Tancredi, 2022). This approach opens new opportunities for resource optimization and continuous improvement in industrial processes, supported by digital advances and device interconnection (Kumar, 2023).

The purpose of this work is to investigate the progress of Machine Learning in industrial environments and its impact on the optimization of production processes. In addition, it analyzes how this technology contributes to improving supply chain management, predicting occupational risks and suggesting preventive measures to promote occupational safety.

It also examines its influence on optimizing and refining manufacturing using 3D printing, as well as its ability to help companies reduce costs. This research offers recommendations that may be of interest to students and academics seeking to better understand ML concepts and applications in various fields of study, as well as to software engineers and developers, entrepreneurs, and managers looking to develop new research and projects in this ever-evolving area.

This study is based on a comprehensive systematic review of the literature, details of which are presented in section 2. The methodology used for this review is described in detail in section 3. Finally, in section 4, a detailed analysis of the information collected is carried out to identify patterns and trends in publications related to the application of Machine Learning in the field of industrial engineering.

2. Literature Review

Before starting with the literature review, it is important to describe each of the fields of application that will be addressed to have a better clarity of the research topic.

Field 1- Machine Learning in Production Systems: Refers to the applications of machine learning techniques within industrial or production environments. It also involves learning models used in industrial environments with the aim of optimizing processes.

Field 2- Machine Learning in the Supply Chain: Refers to the application of ML techniques to analyze data and improve supply chain management. By integrating ML into the supply chain, businesses can reduce costs, improve operational efficiency, and more effectively meet customer needs.

Field 3- Machine learning in industrial safety: ML in industrial safety seeks to improve safety in work environments by analyzing large volumes of data, these systems can identify patterns, predict risks and suggest preventive measures to avoid accidents and improve occupational health. This also helps companies reduce costs, minimize downtime, and protect worker integrity.

Field 4- Machine Learning in Additive Manufacturing: Optimizes and improves manufacturing processes through 3D printing. Machine learning can be used to predict and prevent part defects, optimize resource allocation, and reduce production times. Machine learning also allows businesses to take full advantage of the capabilities of this emerging technology.

Field 5- Machine Learning and inventory control: It involves the use of advanced machine learning techniques and algorithms to manage and optimize inventories across industries. This includes improving inventory replenishment, reducing storage costs, decreasing excess inventory, and preventing product shortages. In addition, it enables automated, data-driven decisions, increasing the efficiency and profitability of the inventory management system.

Field 6- Machine Learning and marketing: It refers to the application of machine learning techniques and algorithms to improve and optimize marketing strategies. By analyzing large volumes of data, machine learning allows you to personalize advertising campaigns, segment audiences more precisely, predict consumer behavior, and optimize ad spend. In addition, it helps identify market trends, improve customer experience, and increase the effectiveness of marketing campaigns through automation and predictive analytics.

2.1. Machine learning in production systems

ML has made its presence known in different fields of engineering such as the mining industry, where it is used to analyze the feasibility of production systems through the intervention of intelligent technology. This application has resulted in a significant improvement in production efficiency.

The use of imputation algorithms, such as Miceforest, have helped to quantify mining feasibility and establish optimal production conditions, contributing to an accuracy rate of 96% (Kang et al., 2023). Another area of engineering that has benefited is the oil industry, where the exploitation of tight oil reservoirs has become economically viable, thanks to the combination of horizontal drilling and multistage hydraulic fracturing. The incorporation of machine learning and big data has enabled the use of evolutionary algorithms to optimize fracturing parameters, such as fracture length, fracture mean, fracture permeability, fracture spacing, and fracture height (Dong et al, 2022). In the petroleum industry, various geological factors are critical to the production of oil in a well. Machine learning is a key tool for identifying these critical factors. Using techniques such as Pearson's correlation tests and sensitivity analysis, aspects such as fluid volumes, saturation, gas condensation, and carbon content are examined. These statistical analyses allow oil companies to develop predictive models and better understand how these factors influence the performance of an oil well (Guo et al., 2021).

In the field of manufacturing engineering, various conventional machine tools such as lathes, milling machines and grinding machines are used to produce mechanical parts. However, innovative technologies have been introduced such as autonomous production machines, to perform the operations automatically.

To improve the ability to forecast predictive maintenance on equipment and components such as the spindle, intelligent learning-based defect detection modules are employed. These modules can anticipate the severity of faults and failures in machines (Schlangenhauf, 2021). In the engineering field, one of the most critical performance indicators for production control is overall equipment effectiveness (OEE). This indicator can combine data from equipment and process performance to improve the quality of the final product. The incorporation of cyber-physical production systems (CPPS) and sensors for data storage facilitates machine learning, maintains optimal performance, improves security, and ensures the quality of results. The accuracy of ML results also depends on the suitability of the algorithms and the quality of the information used (Engelman et al, 2020; Wiemer, 2021).

Artificial intelligence (AI) and ML have increased production capabilities in additive manufacturing in three important areas; One of them is the manufacture of products with complex geometry and shapes, standing out for the effective integration of components, improved performance, and development of compact designs for mobile devices. Another field refers to large-scale customization, applied in the manufacture of small quantities of devices that incorporate high-value components, such as medical devices. The disintermediation of the supply chain is another area, which focuses on the direct production of components, highlighting on-site manufacturing as a crucial element. This enables rapid production in cases of unpredictable demand, especially in products intended for military or medical applications. It is essential to keep in mind that machines used in machine learning use technology that requires supervision and must operate in controlled environments, subject to periodic maintenance schedules (Carpanzo & Togo, 2022). Monitored systems enable efficient capture of system parameters and states in real time, ensuring effective control in manufacturing processes, resulting in an improvement in reliability, data accuracy, and satisfaction for companies (Lee, 2021).

The internet of things (IoT) has transformed industries into smart ones, contributing to the economic development of modern nations by raising living standards and improving working conditions.

Technologies such as 5G, block chain, edge computing and fog computing are helping to solve security challenges by enabling efficient transmission of information, as they make it difficult for digital device systems to be compromised, thanks to data and learning algorithms (Xu, 2023). Another aspect benefited by Machine Learning is the maintenance of production equipment, this process strengthens the continuity of manufacturing or service operations. For the implementation of preventive maintenance to be effective, reliable information from sensors is required to be used in the algorithms and give effective responses, given previous simulations with real data. It is important to consider that the greater the precision required in the processes, the more complex and expensive the solutions should be (Rojek et al., 2023).

In the automotive field, ML is used in the production of vehicles with lightweight materials such as high-strength steels, aluminum, and reinforced thermoplastics (FRP). These materials have contributed to the reduction of fuel consumption and, in the case of electric vehicles, have significantly improved the autonomy (Hürkamp et al., 2020). Thermoplastic materials possess specific mechanical properties that allow large-scale production thanks to short production cycles and efficient cost-benefit ratio (Liebsch et al., 2019).

Industry 4.0 and ML have expanded the possibilities in industrial control systems, enabling a high degree of automation through process modeling and real-time control. This promises to address challenges at all levels of automation, with the goal of controlling industrial production systems (Jamwal et al., 2021). The use of machine learning (ML) algorithms has emerged as a powerful tool for addressing problems and exploring applications in a wide range of areas. The accelerated progress of Industry 4.0 and cloud computing has made it possible to handle huge amounts of data and ML models, thus improving the control of information in production systems and optimizing the identification of parameters in processes (Pereira & Constantin, 2024). Within the framework of Industry 4.0 and its integration with production systems, metal additive manufacturing (AM) stands out, offering a wide variety of industrial applications. Broadly speaking, AM consists of the creation of components by fusing a base material, known as raw material, using a high-powered, localized heat source, which is guided by the information contained in a computer-aided design (CAD) file (Mo et al., 2024).

2.2. Machine learning in the supply chain

The advent of Industry 4.0 has led to the development of technologies that improve supply chain management. These technologies allow manufacturers to track the flow of information using tools that take advantage of available data sources, in addition to using Big Data analytics (BDA) and ML. These tools are essential in supply chain management (Barzizza et al., 2023). The success of organizations in supply chain management depends on collaboration among team members and efficient communication of information. This collaboration has motivated companies to adopt improvements in their operations, such as data analysis, event prediction, and the

proper handling of large volumes of information (Ali et al., 2022).
Another aspect that has been incorporated into ML is cloud-based blockchain technology, which provides a machine learning approach for supply chain management applications, ensuring the sustainability of the process. The adoption of cloud computing has played an essential role in the scalability of blockchains, addressing issues such as availability, storage capacity, latency, and throughput (Wong et al., 2023; Kim et al., 2019).
The current relevance of ML stems from the convergence of various mutually reinforcing trends, making ML an effective tool thanks to the abundance of digital data, which is fundamental to most deep learning algorithms. In addition, another factor that contributes to safer learning and effective decision-making is advanced natural language processing neural networks (Schroeder, 2021; Roh et al., 2019).
Enterprises should be aware of the challenges related to data transformation and manipulation as data transactions in supply chain management networks become more immutable. To effectively manage the large amount of data generated, it is crucial to have a robust cloud infrastructure that offers scalability and Big Data processing. In the maritime logistics domain, systems of this type contribute to risk reduction by guiding cargo ships along planned and safe routes, avoiding deviations and dangerous areas (Wong et al., 2021). To achieve optimal supply chain management, it is essential to rely on statistical evidence and operational research to optimize the fulfillment of product or service demand targets. While the adoption of technologies related to blockchain enhancement is critical (see Figure 1), so is the implementation of a supply chain network designed to predict consumer perception and meet the needs of specific events (Khchine et al., 2018).

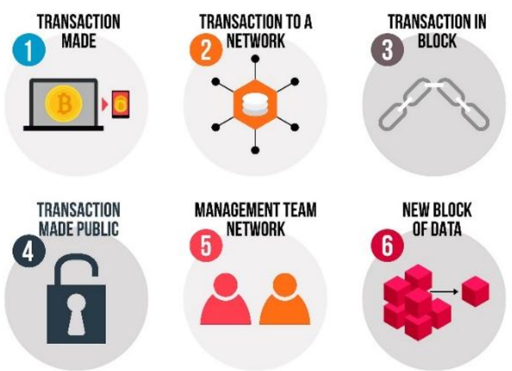

Fig. 1. Blockchain technology.

Supply chain management faces the complex challenges of meeting each phase of supply and demand, compounded by globalization. In response to these challenges, companies are adopting data-driven technologies and machine learning to overcome obstacles in communication channels, distribution times, inventory management, among others (Sani et al., & Kumar, 2023).
For inventory management control, machine learning is used in the use of drones. These devices can locate products on shelves quickly, move light goods, detect cycle inventories, make RFID readings, which increases value in the supply chain. Delivery drones are emerging as a reliable and promising means of transport in this chain (Lei, 2022; Bridgeball, 2023).
Another aspect that has been present along with machine learning is the Internet of Things, which has made notable progress in the logistics field, specifically in warehouse management, communication systems, quality of service and procurement. The application of recurrent neural network models with gates (GRU) and convolutional neural networks (CNNs) has enhanced the ability to anticipate and manage information effectively, reducing users' dependence on constant monitoring of the data sequence (Alzahrani, 2023).
For many SMEs (Small and medium-sized enterprises), implementing the use of technology for supply chain management, as well as to maintain it efficiently, is a challenge and requires the granting of financing. In this sense, in the absence of credit risk predictions from traditional methods, the implementation of machine learning algorithms such as the recurrent neural network and the short-term memory model, has made it possible to efficiently predict to grant and in turn monitor credits, since they can identify fraud, through financial data analysis, economic reports and trends, as well as forecasting consumer and market behavior (Xia et al., 2023). Machine learning also plays a critical role in optimizing the supply chain in the field of biofuels and seed cultivation. Its purpose is to identify methods that ensure efficient material flows between suppliers, warehouses, production facilities, and end customers. Supply chain management has become an essential tool for coordinating all phases of the process, recognizing that any disruption at a specific point can significantly affect the overall performance of the chain (Kim, 2024). In terms of seed cultivation, it is crucial to develop effective non-destructive methods for the classification of millet seed cultivars, with applications in the detection of cultivar contamination that could occur at various points along the cereal supply chain (Ekramirad et al., 2024).

2.3. Machine learning and industrial security

Machine learning has played a critical role in advancing industrial risk assessments during the early exploration, stable development, and high-speed development phases. This has had a significant impact on the safety of workers and the work environment, by allowing more effective monitoring of risks associated with construction and machinery areas, as well as environmental protection (Smith, 2020; Wei et al., 2023).
Another positive aspect in terms of safety for companies lies in the detection of hazards related to landslides. This is achieved through the application of advanced techniques such as neural networks, classification

algorithms, and principal component analysis, as well as the use of inferential and deductive statistical methods. These strategies make it possible to develop an effective methodology for the creation of susceptibility maps, taking into account the specific characteristics of the terrain, which is essential in the proper planning of their use (Tien et al, 2015).

Observation of operations in industrial processes provides the rapid identification of potential faults, which helps to ensure safety in production. Approaches have been developed that integrate techniques such as Fisher discrimination (VWDA), distributed dimensionality reduction in t (t-SNE) and extreme learning (ELM) to carry out visual monitoring of processes. VWDA assigns weights to variables based on their impact on potential failures, represented as vectors. The t-SNE visualizes the characteristics of these vectors, and finally, ELM is used to map the input data to their respective mapping points, thus allowing real-time monitoring of the process (Lu, 2021).

The use of learning algorithms in security applications must address various vulnerabilities, including the verification and interpretation of performance constraints.

There are also training approaches and methods, such as *ML Security Taxonomy*, that can decrease generalization errors, detect attacks in production environments, employ advanced machine learning techniques and diversified strategies (Mohseni et al., 2022).

Another aspect associated with ML is the internet of things (IoT), which is used to identify intruders and threats in the IoT working environment by using deep learning (DLIS). It is important to note that as the number of IoT-connected devices increases, security becomes even more crucial due to the nature of its architecture. Special modules exist that combine optimization algorithms and stacked deep polynomial type networks (SDPNs) to achieve more accurate detection of anomalous data and better performance in terms of accuracy and recall (Otoum, 2021; Kouicem, 2018 & Tariq et al., 2019).

While the implementation of ML and technologies associated with Industry 4.0 has provided benefits that are useful for workers involved in the design and processes of manufacturing and industrial machine systems, it is important to consider the risks associated with artificial intelligence (AI) and ML, along with health requirements. safety and ergonomics that should be considered as part of the safety risk assessment process (Anastasi, 2021). There are various information compaction techniques, also known as custom-made compacted data, that have been applied in various areas of research, including machine learning-based biometrics and statistical analysis for the development of artificial intelligence. This type of compacted data design allows to achieve high accuracy in the data and a reduction in the time in the analysis of the information, adapting to different domains of knowledge. (Yoon et al., 2023 & Song, 2024).

2.4. Machine learning and the additive manufacturing (AM)

In the engineering domain, the expansion of IoT and ML has significantly evolved the demand for location-based services (LBS), machine learning and industrial manufacturing equipment (Rathnayake et al., 2023). Additive manufacturing (AM) is one of the most innovative processes that is based on the extrusion and design of complex 3D parts. In this sense, ML presents a promising approach to identify suitable parameters in the manufacture of parts with the most suitable properties, without the need to analytically model the entire process (Pelzer et al., 2023; Gibson, 2015 & Heng et al., 2024).

Additive manufacturing offers broad design flexibility and the ability to modify material properties. It is important to mention that, in additive manufacturing, a powder bed laser fusion process is used for metals (Khorasani et al., 2020; Ngo et al., 2018), which can give rise to imperfections such as porosity, which can influence the mechanical characteristics of the metal components. Therefore, to improve the accuracy of defect detection, Random Forest models have been developed that are capable of classifying images from micrographs, achieving an impressive 95% accuracy (Altmann et al., 2023). AM has driven notable advances in design, industrial processes, and manufacturing technologies. ML has allowed people to surpass themselves, as they are adapting to new technologies and algorithms that are providing benefits in the execution of tasks and in the analysis of effectiveness in real time for more informed decision making.

Although additive manufacturing is one of the most significant technologies that Industry 4.0 presents to engineering, it is not exempt from failures due to fatigue of equipment components or the presence of defects in the processed parts, which complicates the design process and makes it less precise. These situations, by default, would imply carrying out additional evaluations to determine the existence of said problems in the internal structure of the materials, which would imply expensive experimental tests. All these challenges can be effectively addressed by ML algorithms, which would not only evaluate the limit fatigue but also predict the fatigue of the components. This is how AM has driven remarkable advances in design, industrial processes and ML-driven manufacturing technologies, bringing benefits in the execution of tasks and in the analysis of efficiency in real time (Esoso et al., & Tridello et al., 2023; Sanaei; 2020 & Awd, 2022).

Artificial intelligence (AI) is one of the tools used by researchers to predict the surface quality of materials. Roughness is a complicated and crucial parameter for meeting quality standards, and it has posed challenges in industries such as automotive, aerospace, energy, and product manufacturing, where surface quality influences performance and functionality. While AI helps anticipate surface defects in materials, ML is effective in reducing costs and production time, emerging as a promising and novel technique (Batu, 2023; Pereira, 2019).

Laser-directed fabrications in 3D printing, with a central focus on neural network architecture (CNN), such as VGG16, AlexNet, GooLeNet, and ResNet, are promising, as time information monitoring systems can establish product quality. According to (Patil et al., 2023) the VGG16 architecture can achieve an accuracy of 80% and a recovery rate of 89.3%, making it a reliable option for automating the detection and classification of defects such as gaps, burr formation, and rough texture in parts with additive manufacturing (Zhang et al., 2019).

Design for additive manufacturing (DfAM) is one of the technologies linked to industry 4.0, which drives to continue innovating in engineering, for the use of metal alloys that offer solutions with impact in different areas such as aeronautics, robotics, automotive, among others, and that in turn reduces production costs (Egan, 2023).

Arc flash additive manufacturing (WAAM) can produce large, complex metal components with a high deposition rate. This process can set the right parameters for your operation. In addition, the use of models such as SVR, BPNN, and XGBoost, along with GA and PSO algorithms, facilitates the prediction of these parameters (Zhang et al., 2024 & Sharma et al., 2024).

2.5. Machine learning and inventory control

The integration of machine learning with inventory control (Figure 2) can radically transform inventory management by offering intelligent and adaptable solutions that improve accuracy and efficiency in decision-making. While machine learning is a widely used tool for solving problems, incorporating it into specific use cases with business logic presents numerous challenges. Training, managing, and storing multiple models require the use of a variety of frameworks and programming languages.

Fig. 2. Inventory control elements.

Tools such as SAP and Flextory allow you to calculate orders and play a crucial role in this context. In addition, there are architectures and protocols such as RabbitMQ associated with SAP, which take into account the overall structure of the application and how its components interact. This type of protocol allows the execution of the software to be parallelized and tasks to be distributed, thus achieving greater efficiency (Falkner et al., 2024; Kannisto et al., 2021 & López, 2024). In business, optimization models are used to solve programming problems that include boundary conditions, decision variables, constraints, and target functions. Optimizing information scheduling has become a crucial topic in recent years. Many organizations are looking to improve their facilities to optimize processes and control inventories, aligning with the Industry 4.0 paradigm and optimally managing production systems. Scheduling algorithms and operations scheduling have contributed to increasing the efficiency of organizational processes (Vaccari et al., 2020 & Togo et al., 2022). The Internet of Things (IoT) provides solutions and opportunities for a variety of applications and purposes in areas such as communications, cyberattack analysis, customer service, industrial process management, weather forecasting, traffic flow, inventory control, and targeted marketing. These elements facilitate access to information, which contributes to improving the quality of life of both individuals and industrial workers in various settings, especially in the industrial sector (Hossein et al., 2020 & Ghasemkhani et al., 2022).

There are also inventory models for items with non-instantaneous spoilage that optimize inventory costs, order times, and maintenance costs in a supply chain. There are also mathematical programming methods aimed at efficiently managing the inventory system (Mad et al., 2021).

Machine learning is becoming a crucial tool in inventory control, as it offers the ability to forecast product demand with high accuracy and automate various aspects of inventory management. This translates into a significant reduction in operating costs, minimization of overstocks and stockouts, and improved overall supply chain efficiency. By analysing large volumes of historical and current data, machine learning algorithms can identify patterns and trends that are difficult to detect manually, allowing businesses to make more informed and timely decisions. In addition, the integration of machine learning systems with inventory management platforms facilitates the automation of processes such as product replenishment, stock level optimization, and price adjustment, resulting in a more agile and adaptive operation in the face of changes in market demand.

2.6. Machine learning and marketing

Machine learning and marketing have merged to transform the way businesses interact with their customers and optimize their business strategies. Machine learning is a branch of artificial intelligence that allows machines to learn from data and make predictions or decisions without being explicitly programmed to do so. In marketing, these techniques are used to analyse large volumes of consumer data, identify patterns and trends, personalize advertising campaigns, improve market segmentation, and optimize return on investment. This synergy allows companies to anticipate customer needs and behaviours, offering more relevant and effective experiences.

The fields of artificial intelligence (AI) and machine learning (ML) have had a significant impact on the financial markets thanks to advances in computing and algorithms. These technologies are transforming various sectors, especially the financial sector, optimizing business processes and improving risk management (El, 2023 & Chui, 2016).

Artificial intelligence (AI) has revolutionized high-frequency trading (HFT) by providing advanced tools and algorithms capable of analysing large amounts of data in real-time and making split-second trading decisions. AI enables HFT traders to identify market patterns and trends with unprecedented accuracy and speed, improving the efficiency and effectiveness of their strategies. In addition, the AI's machine learning capability allows these algorithms to continuously adapt and evolve, optimizing their trades and reducing the risk of losses. However, the use of AI in HFT also poses regulatory and ethical challenges, as its speed and complexity can contribute to market volatility and raise concerns about fairness and transparency in financial transactions. There are machine learning algorithms that use deep learning techniques to analyse historical market data, considering factors such as trading volume, differences between supply and demand, and volatility (Arifovic, 2022 & El, 2023).

The complexities of financial markets are often found in patterns and subtle details that conventional statistical models might miss. Artificial intelligence, particularly deep learning models, can identify non-linear relationships in data, which can be crucial for strategies such as high-frequency trading (HFT) (Gomber et al., 2018).

On the other hand, AI algorithms can identify market trends and patterns more quickly than humans, which is particularly advantageous in high-frequency trading, where profit opportunities are brief. One of the most prominent advances in AI is risk management. Advanced algorithms can analyze large volumes of data and detect patterns that might go unnoticed by humans, thereby improving risk assessment and mitigation (Chopra, 2021 & El, 2023).

The incorporation of artificial intelligence (AI) and machine learning (ML) into risk management has brought about transformative change in financial markets, with applications including credit risk assessment, market risk management, and operational risk management. One of the most prominent applications of AI and ML in risk management is credit risk assessment. Traditional models, based on predefined parameters and thresholds, often classify people into rigid credit categories, which can lead to inaccurate evaluations or inappropriate credit decisions. In contrast, AI and ML offer a more dynamic and adaptable approach (Berg, 2019).

Machine learning in marketing has revolutionized the way businesses understand, segment, and communicate with their audiences. By leveraging advanced algorithms, they can personalize experiences, predict behaviours, and optimize strategies more effectively, resulting in more relevant campaigns and a higher return on investment.

3. Materials and methods

For the development of this research, we follow a systematic and transparent process to identify research focused on the target topic. It also involved consulting information from scientific articles, repositories and publishers specialized in the field of machine learning and its applications in engineering. We searched a variety of sources, both in English and Spanish, covering publishers such as Ebsco-essentials, ScienceDirect, IEEEXplore, and MDPI. Table 1 provides a detailed breakdown of the search mechanism used to collect data.

Table 1
Search process to obtain information.

Editorial					
Ebsco-Essentials	Science-Direct	IEEEXplore	MDPI		
Search topics					
Machine learning in production systems	Machine Learning in the Supply Chain	Machine learning in security	Machine Learning in Additive Manufacturing	Machine Learning and inventory control	Machine Learning and marketing
Literature Research Languages					
English			Spanish		
Information analysis					
Search Logical Operators (Algorithms)	Author's name	Magazine name	Year of publication	Keywords	Country of publication or origin

Step 1: Scope of the review. A comprehensive analysis of the relevant literature was carried out, with the aim of exploring existing research on the topic at hand, specifically about reviews on Industry 4.0 and machine learning applications. This process focused on identifying both the inherent challenges and innovative applications that are contributing to continued advancement in engineering. Following the established guidelines for conducting a critical review, our methodological approach was designed to encompass a broad and representative selection of articles, as recommended by Paré et al. (2015). In addition, given the dynamic and ever-evolving

nature of 4.0 technologies, we limited the scope of the review to the most recent publications, covering the period from 1 January 2015 to 03 June 2024.

Step 2: Search procedures. To ensure comprehensive coverage of the research topic, specialized algorithms were employed to retrieve relevant documents from the various relevant publishers, as described in detail in Table 2.

Table 2
Search algorithms for document extraction.

Search Topics	Search Logical Operators (Algorithms)	Ebsco Essential	MDPI	Science Direct	IEEE-Xplore
Machine learning in production systems	AND machine learning and production systems Title AND machine learning Abstract AND machine learning AllFields AND production systems AllFields	55	6	36	14
Machine learning in the supply chain	AND machine learning and supply chain Title AND machine learning Abstract AND machine learning AllFields AND supply chain AllFields	200	12	41	31
Machine learning and industrial security	AND machine learning and industrial security Title AND machine learning Abstract AND machine learning AllFields AND industrial security AllFields	10	13	1	17
Machine learning and additive manufacturing	AND machine learning and additive manufacturing Title AND additive manufacturing Abstract AND machine learning AllFields AND additive manufacturing AllFields	182	5	109	2
Machine learning and inventory control	AND machine learning and inventory control Title AND inventory control Abstract AND machine learning AllFields AND inventory control AllFields	52	20	10	25
Machine learning and marketing	AND machine learning and marketing Title AND marketing Abstract AND machine learning AllFields AND marketing AllFields	50	20	10	5

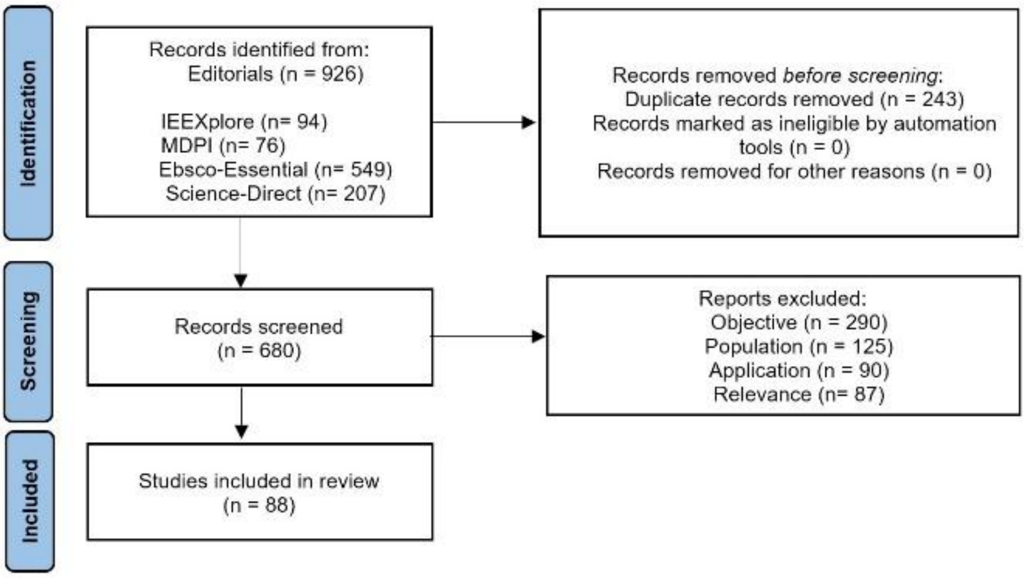

Fig. 3. PRISMA flowchart used to determine the number of papers used in the literature review.

Step 3: Article review and selection process. We chose to use the PRISMA method (Haddaway, 2020) as a starting point to carry out the systematic literature review process. This method uses a flowchart (see Figure 3) as a model for the organized presentation of the information examined. For this research, a review of the initial 926 documents was carried out, prioritizing their importance in relation to the research topic. During this process, 243 documents were discarded due to duplication or similarities, leaving 680 documents. Of these, a comprehensive review was conducted by experts in the field, taking into account criteria such as the objective of the research, the target population, the lack of meaningful application, and its relevance; and 290 documents were excluded because they did not meet the objectives of the research, 125 because they did not fit the target population, 90 because they lacked significant applications in the area of engineering, and 87 because they were not relevant in terms of the information provided. Consequently, only 88 texts were assessed for suitability and inclusion in the systematic review.

The search was based on the collection of information from various sources, such as articles, books, and specialized pages in the fields of research related to Machine Learning (ML) and Industry 4.0 (see Appendix-A). Special attention was paid to publications from the last 10 years, prioritizing the most recent.

Step 4: Bibliometric analysis process and results. In the bibliometric analysis, the word cloud creation approach was applied using the MAXQDA v.2020 software. Literature search is a common practice in current research, as it allows researchers to explore the theoretical underpinnings related to study variables. In the same way, the words that have a greater association with the topic of machine learning are shown, along with the number of documents in which they appear, the impact and the number of highlighted words in total.

For the presentation of the results on the number of publications per year, the statistical software *Origin 2022* was used, which is a program with a high quality in the design of statistical graphs and presentation of results (see Figure 4).

Finally, the number of articles published, the name of the journal where the documents were published and the corresponding citations by year were analyzed. Citation data was obtained through Google Scholar. Of the 88 articles, the 10 most cited articles were identified.

4. Results

4.1. Data review and analysis

At this point, the 2020 edition of the MAXQDA software was used to perform a portion of the qualitative examination of the data. This stage of the analysis focused on generating a visual representation of a set of words from the text, organizing them in a hierarchical structure according to their frequency of use.

The use of the word cloud has made it possible to identify and discern which words are most closely related to the research topic. According to (Chung et al., 2008), word frequency can be considered as a valid measure of the relative importance of words in documents. The word cloud, as a text visualization technique, is especially useful for visualizing the prominence of "keywords" according to their frequency in the text (Xu, 2016).

Figure 4 shows the 40 most frequent words that were used in the search for information in the scientific literature applied in this study.

Fig. 4. Word cloud associated with machine learning.

After identifying the most common words, a second filter was applied to select those that are most closely related to the concept of ML, resulting in 8 keywords. These words are accompanied by information on the number of documents in which they appear, their percentage of impact, and the total count of words detected (see Table 3). The most prevalent word is "Machine learning", which is found in 88 documents with an impact of 89% and is mentioned 6359 times, while the least frequent is "manufacturing", which appears in only 59 documents, with an impact of 53% and 2785 mentions in total.

Table 3
Number of articles and citations

Keywords	Documents	% Documentary Impact	Number of Words
Data	58	66	6603
Machine Learning	78	89	6359
Model	67	76	3019
Used	61	69	2644
Process	65	74	2827
Using	61	69	2639
System	58	66	1448
Manufacturing	59	53	2785

In another analysis, data from the 88 articles were grouped with data from the years 2022 and 2024, as a reference of the most current. The research focused on machine learning as an essential component, its application in engineering has seen significant growth year after year. It is relevant to note that 53% of the total research belongs to the years 2022 and 2023, suggesting that machine learning is an innovative trend in the field of engineering and is being widely adopted as part of Industry 4.0 technologies in various organizations (see Figure 5).

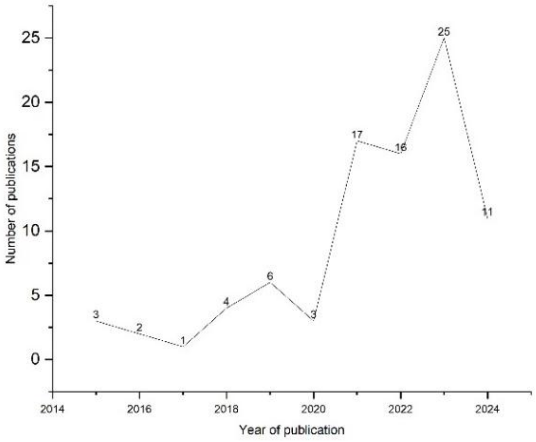

Fig. 5. Number of publications on machine learning and its different applications in engineering.

The year of publication, the name of the journal, the title of the article and the objectives of each of the documents related to the topics associated with machine learning are presented below (see Table 4). Citation data was obtained through Google Scholar. Of the 88 articles, the 10 most cited were identified.

Table 4
Most cited articles related to machine learning

Year	**Journal**	**Article name**	**Research Objective**
2015	Landslides	Spatial prediction models for shallow landslide hazards: a comparative assessment of the efficacy of support vector machines, artificial neural networks, kernel logistic regression, and logistic model tree	Machine Learning Optimization with Susceptibility Mapping
2015	Springer	Additive manufacturing technologies	Trends and developments that comply with ASTM and regulations. Additive Manufacturing Technology and Understanding of Concepts
2016	IEEEXplore	Design principles for industrie 4.0 scenarios	Analysis of Industry 4.0 scenarios based on a qualitative review identifying design 4.0 principles
2016	Production & Manufacturing Research	Machine learning in manufacturing: advantages, challenges, and applications	Presentation of an overview of machine learning techniques available in a manufacturing environment
2017	Springer Nature	Quantum machine learning	Introducing a novel way of looking at quantum physics using machine learning and open-source algorithms
2018	Computer networks	Internet of things security: A top-down survey	Relevant aspects such as cryptographic approaches, safety and security in the field of engineering and private security of the IoT
2018	Composites Part B: Engineering	Additive manufacturing (3D printing): A review of materials, methods, applications, and challenges	To provide a comprehensive review of 3D printing techniques in terms of the main methods employed, materials used, their current status, and applications in various industries.
2019	IEEEXplore	A Survey on Data Collection for Machine Learning	Data acquisition and augmentation models such as an improvement in information management and improvement of data quality through cleaning processes.
2019	Procedia manufacturing	A comparison of traditional manufacturing vs additive manufacturing, the best method for the job	Analysis and review of the capability of additive manufacturing and its current development in establishing quality in today's industry.
2020	Progress in materials science	Defects in additive manufactured metals and their effect on fatigue performance: A State-of-the-art review	Continuous improvement in additive manufacturing as an ideal aid in the machining of parts with a high complexity in their shape

By contrast, in 2015 there were 12,050 machine learning-related citations in papers on neural networks, decision trees, additive manufacturing, and direct digital manufacturing. The year 2018 stood out with 7,190 citations that addressed topics such as the supply chain, the Internet of Things, blockchain, biomaterials, ceramic materials, and metal alloys. Importantly, in the latest publications of 2024, research on artificial intelligence, machine learning, and innovative technologies is already published, which is expected to have a significant impact globally, with numerous citations in future research in the field of engineering (See Figure 6).

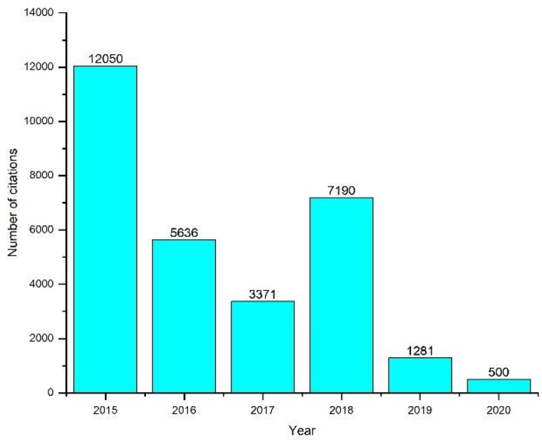

Fig. 6. Number of publications on machine learning and its different applications in engineering.

5. Discussion

The discussion on improving production systems in companies reveals the crucial interdependence between machine learning (ML) and mechatronics within the context of manufacturing systems. As noted by Constantin et al. (2024), automating manufacturing processes has significant potential to increase productivity in various industries. The application of algorithms such as Miceforest, highlighted by Akande (2016) and Li (2020), highlights the fundamental role of accuracy and efficiency in optimizing production conditions. In addition, tool condition monitoring (TCM) systems are essential to ensure the efficiency of machining processes, as Failing et al. (2023) point out.

However, it is in the realm of additive manufacturing that ML shows its true potential. Schlagenhauf (2022) highlights ML's ability to detect anomalies in materials such as 16MnCr5 steel, indicating a significant improvement in error detection and production optimization. In addition, the interconnectedness between technologies such as Blockchain, cybersecurity, AI, and ML, highlighted by Mishara (2023) and Ahmad et al. (2022), demonstrates the importance of a comprehensive digital transformation strategy to ensure data security and reliability in the manufacturing framework.

While the implementation of ML and other emerging technologies presents promising opportunities to improve efficiency and personalization in manufacturing, it also poses significant challenges, such as data quality and complex model interpretation. However, the combination of ML and additive manufacturing promises a profound transformation in the industry, driving innovation and efficiency in the production of high-quality, customized products.

The use of machine learning in inventory control is revolutionizing supply chain management by providing accurate predictions and automated decisions. Machine learning algorithms analyze large volumes of historical sales data, market trends, and demand patterns to anticipate future inventory needs with unprecedented accuracy. This allows companies to optimize their stock levels, reducing both excess and shortage of inventory. In addition, machine learning techniques can be continuously adapted and improved, learning from new data inputs to adjust their predictive models. As a result, businesses can improve their operational efficiency, reduce costs, and increase customer satisfaction by ensuring products are available when and where they are needed.

Machine learning is transforming marketing by enabling highly personalized and efficient strategies. By analyzing large volumes of consumer behavior data, such as purchase histories, social media interactions, and web browsing, machine learning algorithms can identify patterns and segment audiences with great accuracy. This makes it easier to create targeted marketing campaigns that resonate more with consumers' individual interests and needs, increasing conversion rate and customer loyalty. In addition, machine learning optimizes the allocation of advertising budgets by predicting which channels and messages will be most effective. Real-time analytics capabilities enable dynamic adjustments to marketing strategies, continuously improving their effectiveness.

6. Conclusion

In engineering, machine learning has become a disruptive technological innovation that is changing the way businesses face various challenges in different fields. This revolutionary branch of artificial intelligence is based on the ability of computers to process large amounts of data, allowing patterns to be identified and better decisions to be made, rather than relying on explicit programming. In this context, ML has become an essential tool for engineers, helping to optimize processes and create smarter and more efficient systems.

In areas such as manufacturing, logistics, and supply chain, ML algorithms can analyze data in real-time to identify inefficiencies, forecast machinery failures, and thus intervene effectively so as not to affect product quality. This promotes the execution of preventive maintenance, which translates into significant resource savings and increased productivity.

In the field of mechanical engineering, machine learning is applied in product design and manufacturing, where computer-aided design creates more accurate and resilient products, considering various factors, such as performance, durability, and cost.

In addition, machine learning plays a critical role in software engineering, helping to detect vulnerabilities, contributing to the development of more secure systems, maximizing performance, and automating testing and debugging processes.

In short, machine learning has transformed engineering by providing machine scientists with powerful tools that allow them to free themselves from monotonous tasks, focusing on those that are most relevant and with more insightful solutions. It is crucial to note that artificial intelligence may not currently address all scenarios in the same way as a human being, but it continues to advance by leaps and bounds improving the quality of life globally. Collaboration between engineers and data scientists is essential to realize the full potential of this technology and successfully address future challenges.

Machine learning stands out as a crucial tool in inventory control, as it makes it possible to forecast product demand with high accuracy and automate key aspects of inventory management, reducing operating costs, minimizing overstocking and shortages, and improving overall supply chain efficiency. By analysing large volumes of data, these algorithms identify patterns and trends that are difficult to detect manually, facilitating more informed and timely decisions. The integration of machine learning systems with inventory management platforms automates processes such as product replenishment, stock level optimization, and price adjustment, resulting in a more agile and adaptive operation in the face of changes in market demand.

In the financial markets, artificial intelligence (AI) and machine learning have revolutionized areas such as high-frequency trading (HFT) and risk management. Advanced AI tools and algorithms make it possible to analyse large amounts of data in real-time and make trading decisions in fractions of a second, improving the efficiency and effectiveness of trading strategies. In addition, these technologies make it possible to identify patterns and trends more accurately, optimize operations, and reduce the risk of losses. However, the use of AI in HFT also poses regulatory and ethical challenges, such as market volatility and concerns about fairness and transparency in financial transactions.

The application of machine learning and artificial intelligence in marketing and finance has allowed companies and markets to improve their strategies, optimize processes and offer more personalized and efficient experiences, although it also brings with it important challenges that must be addressed.

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