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Machine learning in industrialization: a bibliometric analysis

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Abstract
Machine learning is currently emerging as one of the most rapidly advancing technologies, with a recent upward trend in its use for process automation across industrial processes. The objective of this study was to conduct a bibliometric analysis to identify research trends in machine learning. The Scopus database was used to identify scientific production. Bibliometric indicators of visibility, impact, and concurrence were analyzed. The analysis of 7,335 documents, involving 22,383 authors, showed a growth rate of 20.86% from 1988 to early 2024. Three dominant research trends were identified: the first based on machine learning applications in industrial processes, the second referring to the human factor and artificial intelligence, and the third related to convolutional neural networks.

Keywords: machine learning; industrialization; bibliometrics; artificial intelligence; supervised learning; unsupervised learning; reinforcement learning.

Aprendizaje automático en la industrialización: un análisis bibliométrico

Resumen:
El machine learning es una de las tecnologías en auge actualmente, en los últimos años se ha observado una tendencia en su uso en la industria para la automatización de procesos. El objetivo de este estudio fue desarrollar un estudio bibliométrico para identificar las tendencias de investigación sobre machine learning en la industrialización. Se utilizó la base de datos Scopus para la identificación de la producción científica. Se analizaron indicadores bibliométricos de visibilidad, impacto y concurrencia. El análisis a partir de 7335 documentos, con la participación de 22383 autores, evidenció un crecimiento con una tasa de 20.86% en el intervalo de tiempo desde 1988 hasta inicios de 2024. Se identificaron tendencias dominantes al tema de investigación: la primera basada en la industria y el machine learning la segunda referida al factor humano y la inteligencia artificial, y la tercera relacionada con las redes neuronales convolucionales.

Palabras clave: aprendizaje automático; industrialización; bibliometría; inteligencia artificial; aprendizaje supervisado; aprendizaje no supervisado; aprendizaje reforzado.

1 Introduction

Artificial intelligence (AI) is defined as the simulation of human intelligence processes by machines, especially computer systems [1].

Regarding their applications in industry, the use of Graph Neural Networks (GNNs) is transforming multiple industrial sectors, particularly in transportation, finance, and telecommunications. In intelligent transportation systems, GNNs model spatial and temporal dependencies, improving traffic prediction and resource optimization [39]. Additionally, GNNs are related to ML as an advanced model within the framework of deep learning [39].

On the other hand, in the financial sector, deep learning processes complex data to predict markets and enhance strategic decision-making, demonstrating the cross-sector versatility of these tools in areas such as logistics [40].

Meanwhile, in telecommunications, GNNs optimize the

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management of complex networks and resources such as spectrum and routing, showcasing their ability to capture advanced dynamics [41].

Within this field, machine learning (ML) stands out as a decisive branch that focuses on developing algorithms and statistical models, enabling computers to learn and make predictions based on data [2].

ML is generally classified into three main categories: Supervised learning (SL), Unsupervised learning (UL), and Reinforcement learning (RL) [3].

SL is one of the categories within ML, based on a model trained with a labeled dataset. In this approach, the model is trained with both input and output data. Once trained, it can be used to predict outputs from new inputs not seen during training [4].

UL, on the other hand, is based on unlabeled data. This approach focuses on identifying inherent patterns or structures in the data, without the explicit guidance of known inputs and outputs during model training [5].

As for RL, the focus is not on labeled or unlabeled datasets. Instead, it concentrates on how an agent can make sequential decisions to maximize some notion of "reward" [6]. Additionally, it can be stated that deep learning, thanks to its multiple applications, can be used in various ways within these three categories: “SL”, “UL” y “RL”. [39]

This field is not only growing in significance but has also become a major catalyst of growth across industrial processes due to its ability to drive efficiency, innovation, and competitiveness. ML has revolutionized numerous sectors by enabling the automation of complex tasks, process optimization, and more informed decision-making. This technology is achieving significant transformations, from healthcare to manufacturing to logistics, providing opportunities to improve quality, reduce costs, and accelerate product and service development [7].

Industrialization is defined as the process by which mass production systems are developed and established to meet society's needs and demands and is paramount in the world of today This process involves adopting advanced technologies, optimizing resources, and efficiently organizing labor for the large-scale manufacture of goods and services [8].

This is a crucial current topic as it contributes to the achievement of the United Nations Sustainable Development Goal 9: "Build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation" [9]. Specifically, it supports target 9.2: "Promote inclusive and sustainable industrialization and, by 2030, significantly raise industry's share of employment and gross domestic product, in line with national circumstances, and double its share in least developed countries" [9].

For instance, [36] highlights the extensive growth of AI and ML, illustrating their relevance to each of the Sustainable Development Goals (SDGs) in various ways. These technologies have demonstrated applicability across fields such as industrialization, environmental pollution, and economics. This underscores the expanding reach of ML and AI into numerous domains.

On the other hand, [37] focuses on their application in more specific fields, such as business. It reveals a growing trend in the development and implementation of techniques and methods involving ML and AI, which are rapidly gaining momentum and widespread adoption.

Lastly, [38] showcases the diverse applications of ML, reaffirming its broad scope of study and practical use. As previously discussed, this versatility indicates that ML is a field poised for continued growth and expansion.

The importance of conducting an analysis of this nature lies in the increasing proliferation of specialized articles on ML and AI [36]. Given the rapid generation of data in these fields, it is essential to establish methods for quantifying and organizing this information systematically. Such reviews can play a pivotal role in strengthening the theoretical foundation for future research, enabling the identification of data sources and the extraction of relevant information in a structured manner [36].

In summary, ML emerges as a fundamental tool for improving efficiency, productivity, and sustainability in various industrialization sectors. This position is reflected in the large number of publications on the subject, with a total of 7,335 associated articles as of April 2024 in Scopus. It is therefore appropriate to examine this topic using bibliometric analysis, a widely recognized and rigorous method that allows for the analysis and representation of large volumes of scientific data [10].

This article presents a bibliometric analysis of the application of ML in industrialization, with the objective of analyzing its evolution, trends, and areas of application, as well as identifying relevant actors in this specific topic. It also presents a summary of the 15 most cited research articles in this area of study. It is worth noting that this study represents a novel case that has not been previously conducted.

After this introduction, the article is organized as follows: section 2 presents the methodology used, section 3 the results, and section 4 the discussion and conclusions.

2 Methodology

This study employs a bibliometric analysis to examine the application of ML in industrialization. Data was collected from the Scopus database, providing a comprehensive overview of the field.

The search was conducted on April 26, 2024, using Scopus to identify English-language journal articles on ML in industrialization. The following search equation was used:

(TITLE-ABS-KEY (“ML”) AND TITLE-ABS-KEY (industrial*)) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (LANGUAGE , "English"))

This search yielded 7,335 articles, which formed the basis of our bibliometric analysis. The Bibliometrix library in R Studio [11] was used to analyze the following categories:

- Main data: Including number of sources, authors, and annual growth rates.
- Scientific Production: Annual publication rates.
- Citation analysis: Examination of the 10 most globally cited articles and their annual citation rates.
- Most relevant papers: A summary and categorization of the 15 most relevant research papers, based on the classification proposed by [3].
- Thematic Map: Analysis of niche topics within the research field.
- Co-occurrence Network: Analysis of the most frequent keywords.

- Factor Analysis: Identification of research clusters.
- Scientific affiliations: Analysis of the most prolific institutions.
- Country-level production: Examination of scientific output by country.
- Three-field plot: Analysis of the relationships between authors, references, and keywords.

In general, the analysis provides an overview of the subject under study.

Exclusion criteria were applied to focus the analysis. Only English-language 'articles' were considered, excluding other document types. For the in-depth article analysis, additional criteria were applied, such as excluding literature reviews or articles with a generalized treatment of ML that didn't provide specific structural insights.

On the other hand, the article was structured as follows:

In Fig. 1, we can see the structure of this article, which is divided into three sections, each with its specific components. In the introduction section, we will cover everything from the abstract to the introductory part of the article. The second part will analyze the results found through various graphs and tables, and finally, in the conclusion, a discussion will be provided, followed by the references.

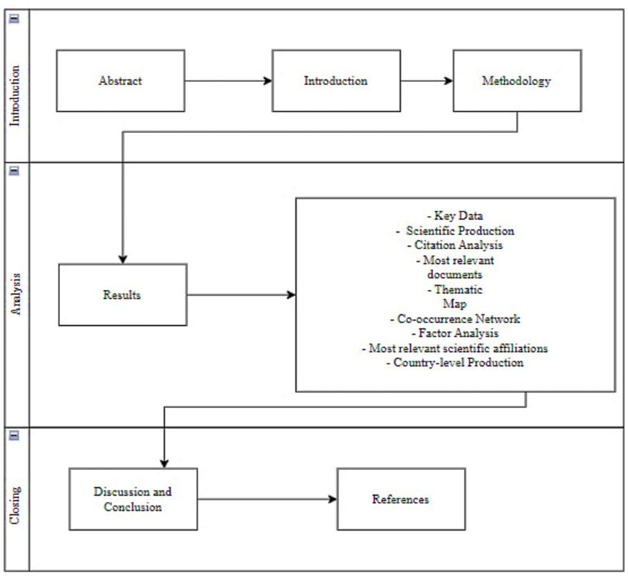

Figure 1. Article Structure Flowchart.
Source: Own elaboration.

The methodology consists of four phases, as illustrated in Fig. 2. Phase 1 involves conducting a search in the Scopus database. Phase 2 focuses on data collection, followed by Phase 3, which is dedicated to analyzing the collected data. Finally, Phase 4 encompasses drawing conclusions and assessing the limitations of the study.

Finally, it is worth noting all tables and figures presented in this study were created by the authors based on the data found.

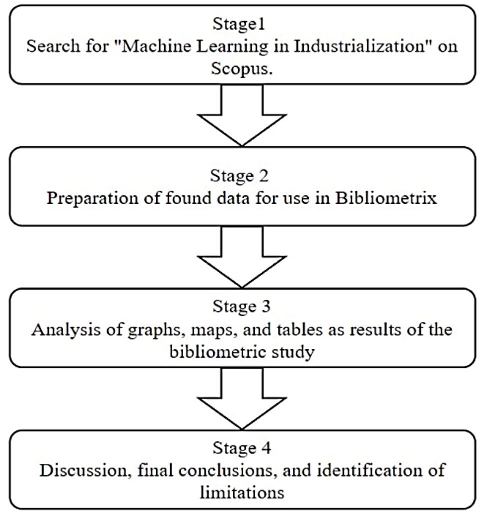

Figure 2. Phases of the methodology
Source: Own elaboration.

3 Results

This section presents the findings from our bibliometric analysis, organized according to the categories outlined in the methodology.

3.1 Key Data

Table 1 presents the overall results of the dataset. The analysis encompassed 2,149 sources published between 1988 and April 2024, with an average annual growth rate of 20.86%. The dataset comprises 7,335 documents. The relatively young average age of the articles (2.89 years) in our sample suggests that this is an emerging field with significant potential for future research.

Table 1.
Summary of most important data

Description	Results
Timespan	1988:2024
Sources (Journals, Books, etc)	2149
Documents	7335
Annual Growth Rate %	20.86
Document Average Age	2.89
Average citations per doc	19.3
References	335959
Documents Content	
Keywords Plus (ID)	34231
Author's Keywords (DE)	17960
Authors	
Authors	22383
Authors of single-authored docs	272
Authors Collaboration	
Single-authored docs	284
Co-Authors per Doc	4.62
International co-authorships %	30.47
Document Types	
Article	7335

Source: Own elaboration.

3.2 Scientific Production

Fig. 3 illustrates the annual scientific production trend. Publications are distributed across 2,149 different sources, involving 22,383 authors. The analysis reveals a clear upward trend, particularly pronounced from 2015 onwards, and significantly more than the single document published in 1988. The peak was reached in 2023 with 1,916 publications. As of April 26, 2024, 916 papers have already been published this year. If this trend continues, it is possible to project a 30% increase in publications by the end of 2024 compared to 2023.

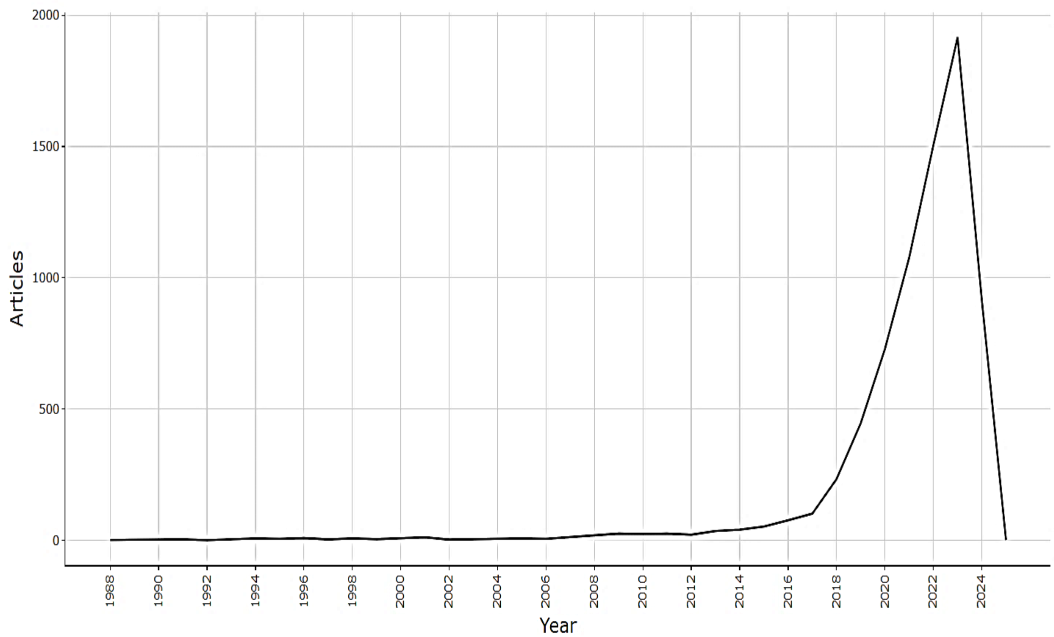

Figure 3. Annual Scientific Production.
Source: Own elaboration.

3.1 Citation Analysis

Table 2 shows the annual citation counts for the top ten highly cited scientific articles. The highest counts suggest considerable impact in their respective fields of research. For example, article [12] has the highest annual average of 393.29 citations, indicating significant and continuing influence. Other notable articles include [13] with 267.75 citations and [14] with 213.20 citations. In contrast, some articles, such as [15] with 71.44 citations per year, the lowest count, show a moderate annual average, which may suggest a lower influence or a decrease in their impact over time.

It is important to note that these articles, except for [14], were not considered among the sample. This is because many of these focus on literature reviews, such as [12], which discusses Explainable AI (XAI), and [16], which reviews fault detection and diagnosis methods. Others like [15] and [17], although they address artificial intelligence-related issues, do not present direct applications of ML in their studies. [15] focuses on authorship attribution, while [17] deals with Digital Twin. Finally, [18] and [19], although they include ML components, focus mainly on optimization frameworks and secure data exchange architecture, respectively.

Table 2.
Total number of citations of the most globally cited documents per year

Paper	Title	TC per Year
[12]	Peeking Inside the Black-Box: A Survey on Explainable Artificial Intelligence (XAI)	393.29
[16]	Survey on data-driven industrial process monitoring and diagnosis	93.38
[15]	A survey of modern authorship attribution methods	71.44
[20]	Deep learning for smart manufacturing: Methods and applications	158.86
[13]	Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy	267.75
[14]	On hyperparameter optimization of ML algorithms: Theory and practice	213.20
[21]	A deep convolutional neural network with new training methods for bearing fault diagnosis under noisy environment and different working load	144.86
[17]	Digital Twin: Enabling Technologies, Challenges and Open Research	191.60
[18]	Pymoo: Multi-Objective Optimization in Python	158.60
[19]	Blockchain and Federated Learning for Privacy-Preserved Data Sharing in Industrial IoT	139.40

Source: Own elaboration.

3.2 Most relevant documents

In this section, Table 3 summarizes the 15 most relevant scientific articles according to Scopus, selected from the total 7,335. Each article is briefly summarized and categorized according to the classification proposed by [3], highlighting whether it focuses on SL, UL, or RL.

3.3 Thematic Map

Fig. 4 illustrates the thematic map of ML in industrialization. Topics such as 'Internet of Things', 'network security', and 'anomaly detection' show high development but low relevance marking them as niche topics. There are no topics that can be labeled as emerging or declining, nor as driving themes, which would be those of high relevance and development. In the core topic quadrant, key topics such as 'ML', 'forecasting', and 'AI' demonstrate high relevance but lower development, suggesting areas ripe for further research. The chart also includes the terms 'article', 'human', and 'algorithm', positioned relative to the axes, indicating a cross-cutting theme or specific focus in the analysis.

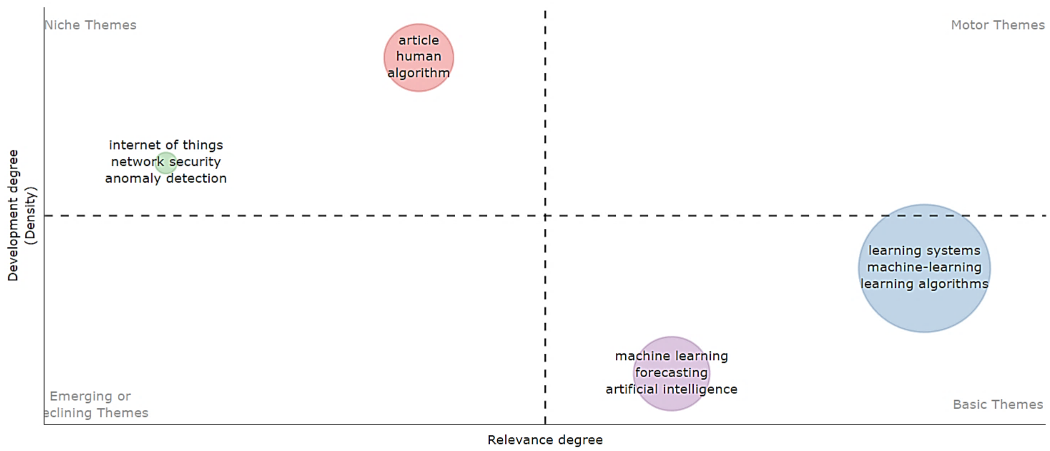

Figure 4. Thematic Map
Source: Own elaboration.

Table 3.
Most relevant articles

Art.	Summary	Type
[22]	Proposes an autonomous platform designed to automate ML processes based on specific levels of autonomy for various industries, including information management and smart cities.	SL
[23]	Explores the application of ML techniques on the Internet of Things (IoT) field to improve connectivity and communication in the smart city industry.	SL
[24]	Addresses the application of ML techniques to predict and improve the efficiency of corrosion inhibitors in metals. It is mainly applied to the materials industry.	SL, UL, RL
[25]	Describes how ML is applied to predict the reliability of manufacturing components compared to traditional approaches, targeting the manufacturing industry.	SL
[26]	Analyzes the use of ML to classify plant leaf diseases, with applications in the agricultural industry.	UL
[27]	Addresses the use of statistical and ML models to predict failures in manufacturing robotic arms. This work applies to the automation and robotics industry.	SL
[28]	Discusses how ML accelerates the development of quantum dots, which are crucial nanometer materials for advanced photonics technology. This work is primarily applicable to the materials science industry and photonic device engineering.	SL, UL
[14]	Discusses techniques for hyperparameter optimization in ML algorithms, such as Bayesian optimization and metaheuristic algorithms. It is relevant to the ML and AI industry.	SL, UL
[29]	Discusses how ML and AI are transforming various industries by providing insights into how ML techniques are applied to fields such as engineering, life sciences, finance, and sports analytics.	SL, UL, RL
[30]	Investigates the use of ML-based models to improve timber allocation planning in sawmills. Applies to the forest industry, specifically in the forest products supply chain.	SL
[31]	Presents a hybrid ML (HML) model for complex manufacturing information systems. This work is relevant to the manufacturing and production control industry.	UL
[32]	Describes the implementation of courses that integrate ML concepts into the operations research curriculum. This initiative is relevant to the education sector, specifically in the training of engineers and professionals in analytics and optimization.	UL
[33]	Focuses on the reliability assessment of WC-Co-based cemented carbides using ML. It is relevant to the manufacturing industry.	UL
[34]	Addresses the use of ML methods to develop customized models of the human neuromusculoskeletal system. The industry to which it is mainly applied is biomedical, orthopedic, and rehabilitation technology.	SL
[35]	Focuses on predicting the success of startups using an ML approach. A model is proposed that considers both internal conditions of startups and industry characteristics to make accurate predictions. This study is applicable to the business and entrepreneurship industry.	UL

Source: Own elaboration.

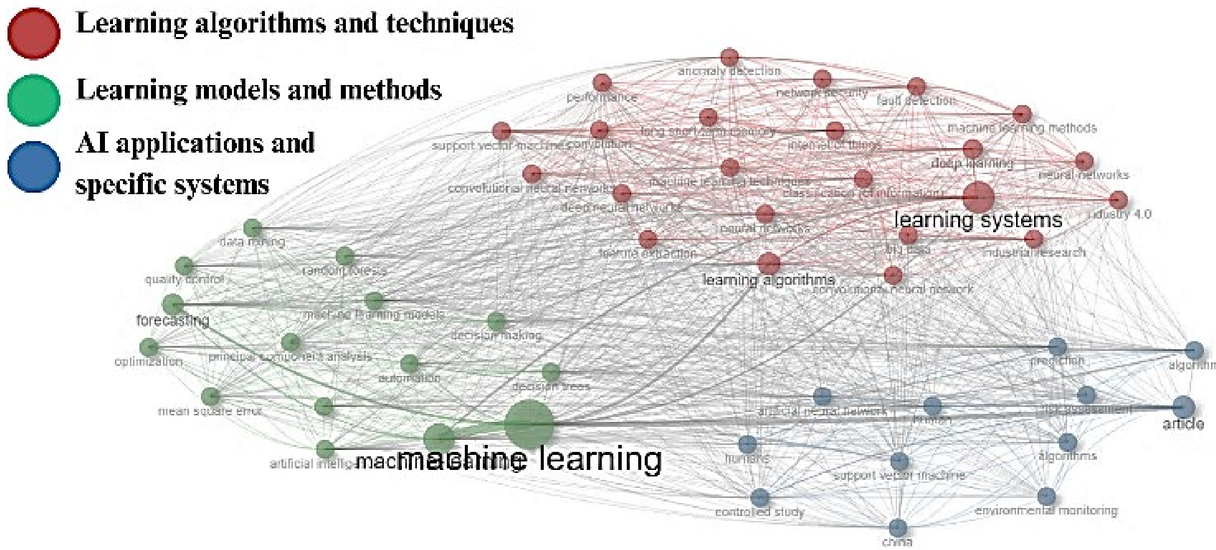

Figure 5. Co-occurrence Network
Source: Own elaboration.

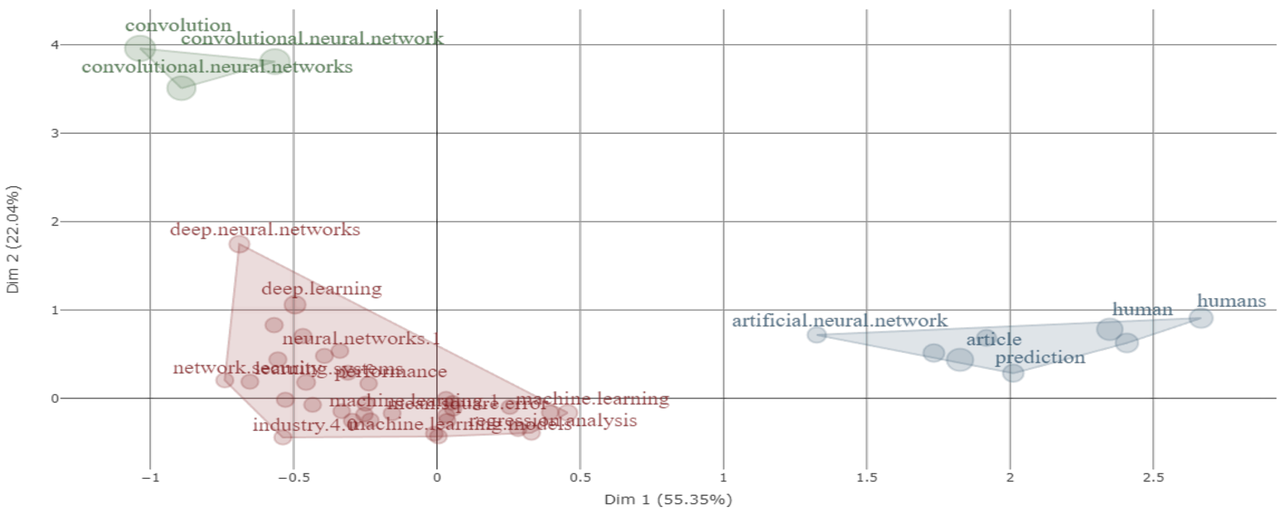

Figure 6. Factor analysis.
Source: Own elaboration.

3.1 Co-occurrence Network

Fig. 5 illustrates the co-occurrence network of keywords, generated using a bibliometric network construction and visualization tool. The terms with the highest frequency are ‘ML’, ‘industry’, ‘innovation’, and ‘infrastructures’. The analysis revealed three main clusters: green, blue and red.

The green cluster contains terms related to AI techniques and models, such as ‘ML techniques’, ‘random forests’, ‘learning algorithms’, ‘ML models’, ‘automation decision’, and ‘artificial neural network’. These terms suggest that the network focuses on various ML approaches and models.

The blue cluster is primarily centered around neural network including terms such as ‘neural networks’, ‘convolution’, ‘convolutional neural networks’, ‘information classification’, and ‘feature extraction’ indicating the network is particularly interested in the applications of neural networks to feature extraction, classification, and evaluation.

Finally, the red cluster focuses on learning systems and ML techniques as it includes terms such as ‘learning systems’, ‘ML’, ‘SL’, ‘UL’, ‘RL’, 'classification', ‘prediction’, ‘control’, ‘learning algorithms’, ‘forecasting’, ‘set theory’, and ‘machine’.

3.2 Factor Analysis

Fig. 6 presents a factor analysis based on multiple correspondence analysis. In the graph, each color represents a group of words that address a specific theme or subfield. The analysis identified three dominant clusters with respect to the research topic. The first (green), although the least relevant, addresses factor convolution. The second (red), and the most relevant, groups terms aligned with ML such as deep learning and neural networks. Finally, the last subgroup (blue) brings together human-related terms such as ‘humans’ and ‘article’, among others.

3.3 Most relevant scientific affiliations

We identified 1,589 different affiliations, with Zhejiang University (274 articles) being the most prolific, followed by University of California (188 articles), Northeastern University (171 articles), University of Science and Technology Beijing (163 articles), Tsinghua University (160 articles), Huazhong University of Science and Technology (144 articles), Central South University (131 articles), Beijing (129 articles), Shanghai Jiao Tong University (106 articles), and 123 papers affiliated to others institutions.

3.4 Country-level Production

Fig. 7 illustrates the global distribution of scientific production in a range of blues, where the most intense blue indicates the regions with the highest number of scientific

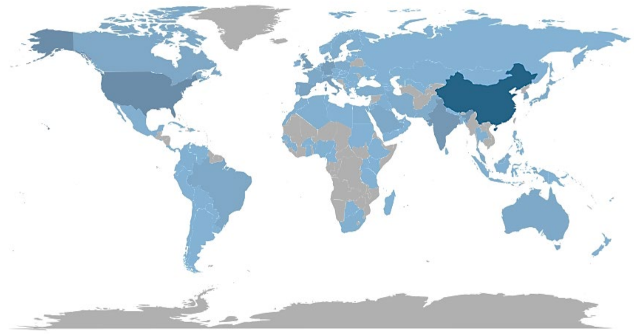

Figure 7. Scientific production by country
Source: Own elaboration.

affiliations, while the gray color indicates the absence of scientific production in this topic. China (8,562 articles) and the United States (3,492 articles) lead in contributions followed by India (2,224 articles), United Kingdom (1,609 articles), Germany (1,602 articles), Italy (1,392 articles), Spain (1,054 articles), South Korea (1,037 articles), Canada (772 articles), and Brazil (770 articles). Brazil stands out as the Latin American country with the most publications on the subject.

3.5 Three-field Plot

Fig. 8 establishes a relationship between authors, keywords, and references.

The left column shows important references with a high level of relationship with ML and deep learning. Some authors that stand out are Breiman, LeCun, Bengio & Hinton, and Kingma & Ba.

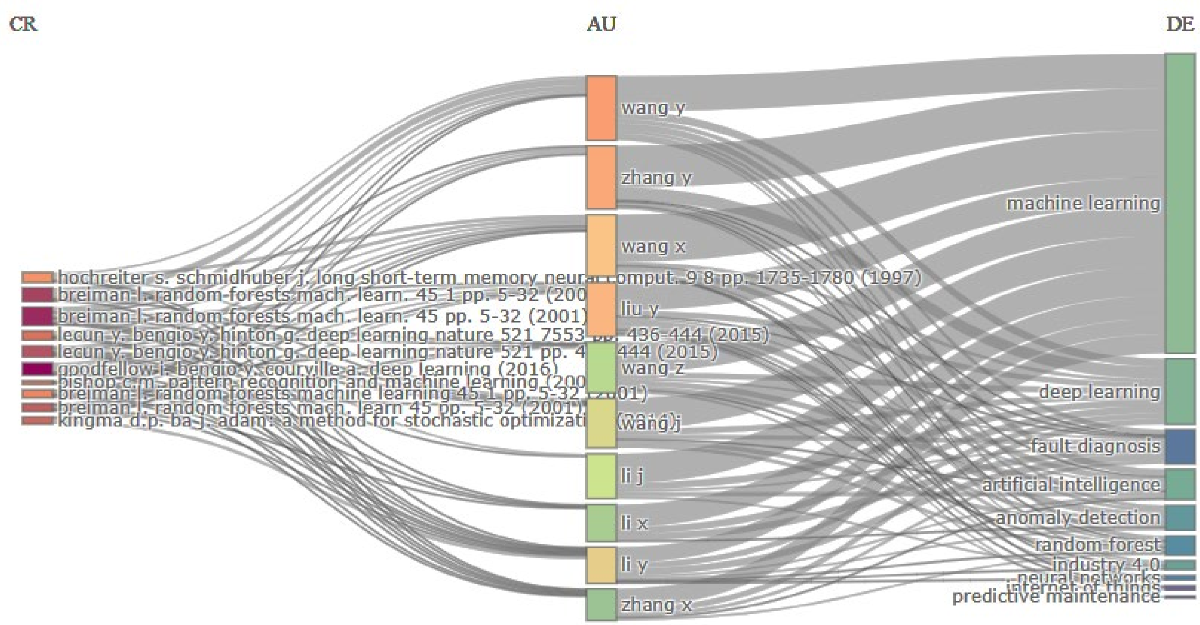

Figure 8. Three-field plot of authors, references and keywords
Source: Own elaboration.

The middle column shows authors such as Wang Y, Zhang Y, and Wang X, who display a connection to multiple references and keywords.

The column on the right shows the keywords associated with the articles of these authors, the most relevant words being ‘ML’, ‘deep learning’, ‘fault diagnosis’, ‘AI’, ‘anomaly detection’, ‘random forest’, ‘long short-term memory (LSTM)’, ‘industry 4.0’, ‘neural networks’, and ‘predictive maintenance’.

The relationships between CR (Cited References), AU (Authors), and DE (Keywords) show a dense network of interconnections where fundamental references in ML and deep learning significantly influence the research of several leading authors, who in turn work on a variety of key applications and technologies in these fields.

1 Discussion and Conclusion

The bibliometric analysis conducted on the application of ML in industrialization has revealed several significant trends and findings.

As of April 2024, 7,335 articles have been identified in Scopus. According to Fig. 3, scientific production in the field of ML applied to industrialization began to show significant growth starting in 2015. This growth became especially pronounced from 2019 onwards, peaking around 2023. Put in numbers the growth experienced since 2015 to April 2024 is 20.86%. This remarkable increase in the production of scientific papers may indicate a growing interest and investment in the application of ML techniques across industrial processes, as well as their adoption and application of ML methods, reflecting a continued expansion and growing interest in this area of research. There seems to be a deep interest of the scientific and technological community.

The Three Field Plot analysis identified Wang Y. and Zhang Y. as particularly influential authors who have published widely cited works. Additionally, methodologies such as ‘Long Short-Term Memory (LSTM)’, ‘random forests’, and ‘deep learning’ emerged as crucial in this field.

The thematic map highlighted ‘learning systems’ and ‘learning algorithms’ as fundamental yet underdeveloped areas, suggesting significant opportunities for future research.

As for the factor analysis, three relevant subthemes could be identified: ML, AI, and convolutional neural networks. The first of these subthemes is the most relevant due to the high frequency of associated words in the graph. In addition, the field covered by convolutional neural networks has the fewest synonyms of the three, while the field covered by ML has the most.

Regarding the production of scientific articles by country, there was a low presence of research in Latin America. Although Brazil's presence among the most outstanding countries was evident it is in the last position with 770 scientific articles.

Regarding the limitations of the present analysis, three main aspects were identified. First, only articles indexed in Scopus were included due to lack of access to other databases, which restricted the scope of the review. Secondly, the language selected was a limitation, as only articles in English were considered, excluding publications in other languages that could have provided relevant information. Finally, the exclusive use of articles as a data source also represents a limitation, since other types of documents that could have enriched the analysis were omitted. These three factors limited the breadth and diversity of our sample.

In conclusion, we can say that ML has contributed significantly to industrialization and, over time, will automate more processes and handle larger amounts of data. Industries will have to adapt to these advances, conducting more tests and collecting larger amounts of data to achieve greater accuracy and improve their contributions. However, the lack of empirical studies and long-term evaluations of the proposed applications represents a notable opportunity for improvement, as most of the techniques and applications described appear to be in experimental or proof-of-concept phases, without sufficient evidence of their effectiveness and sustainability in real and long-term scenarios. Knowledge and familiarity with key concepts such as IoT, neural networks, learning systems, and forecasting will allow industries to better manage their data and achieve greater efficiency, since over time there will be greater changes and it will be necessary to adapt to and understand these advances.

In addition, it is recommended to implement studies such as Systematic Literature Review (SLR) and State of the Art Systematic Review (SotA) to obtain a comprehensive and up-to-date view. In addition, Systematic Mapping Review (SMR) and Scoping Review will categorize and explore the breadth of research, consolidating existing knowledge and guiding future research.

It is suggested to analyze articles from other repositories such as Web of Science (WOS) and SciELO, among others, to obtain a broader and more diverse perspective of the literature. It is also recommended to conduct specific studies on topics identified as emerging or insufficiently explored during the review, such as specific applications of RL, IoT and ML integration, and the impact of ML on industrial sustainability, to deepen knowledge and potential practical applications.

In the context of ML applied to industrialization, various challenges and opportunities are identified that outline future lines of research. Many applications described in the literature are in experimental or proof-of-concept stages, which limits their validation in real scenarios. In addition, ML methodologies face difficulties in adapting to the variability of data and operating environments characteristic of industrial contexts, which poses the challenge of generalizing solutions and ensuring their integration with existing technologies.

For example [43], highlights 2 challenges. First, many algorithms have been validated mainly through simulations with synthetic data, which makes it difficult to consolidate them in practical environments. Second, deep learning-based algorithms often require large volumes of data for training, which represents an obstacle for organizations that do not have sufficiently large and representative data sets.

On the other hand, there are significant opportunities for the development of ML in industrialization. These include the expansion of applications in emerging sectors, such as industrial sustainability, energy efficiency, and waste management. In addition, the integration of ML with the IoT could improve automation and real-time monitoring, while CNN offer great potential for specific applications, as seen in factor analysis.[42]

Finally, the expansion of research in less explored regions represents an opportunity to generate unique perspectives tailored to local needs. In Latin America, for example, Brazil leads in scientific production, which underlines the importance of promoting similar studies in other countries in the region. In conclusion, overcoming these barriers and taking advantage of these opportunities could significantly contribute to technological progress and competitiveness in various industrial sectors.

References

[1] McGenity, C., Clarke, E.L., Jennings, C., Matthews, G., Cartlidge, C., Freduah-Agyemang, H., Stocken, D.D., and Treanor, D., Artificial intelligence in digital pathology: a systematic review and meta-analysis of diagnostic test accuracy. NPJ Digit Med, 2024. DOI: https://doi.org/10.1038/s41746-024-01106-8

[2] Šuc, D., Vladušič, D., and Bratko, I., Qualitatively faithful quantitative prediction. Artif Intell, 158(2), pp.189–214, 2004. DOI: https://doi.org/10.1016/j.artint.2004.05.002

[3] Ganjare, S.A., Satao, S.M., and Narwane, V., Systematic literature review of machine learning for manufacturing supply chain. TQM Journal, 2023. DOI: https://doi.org/10.1108/TQM-12-2022-0365

[4] Saleh, O., Otim, F.N., and Otim, O., Application of supervised learning classification modeling for predicting benthic sediment toxicity in the southern California bight: a test of concept. Science of the Total Environment, 901, art. 165946, 2023. DOI: https://doi.org/10.1016/j.scitotenv.2023.165946

[5] Kruglov, A.V., The unsupervised learning algorithm for detecting ellipsoid objects. Int J Mach Learn Comput, 9(3), pp.255–260, 2019. DOI: https://doi.org/10.18178/ijmlc.2019.9.3.795

[6] Keshavarz-Haddadha, P., Rezvani, M.H., Molla-Motalebi, M., and Shankar, A., Machine learning methods for service placement: a systematic review. Artif Intell Rev, 57(3), art. 10684-0, 2024. DOI: https://doi.org/10.1007/s10462-023-10684-0

[7] Breque, M., De Nul, L., Petridis, A., Industry 5.0: towards a sustainable, human-centric and resilient European industry. Publications Office of the European Union, DOI: https://data.europa.eu/doi/10.2777/308407

[8] Shi, Y., Hu, J., Shang, D.T., Liu, Z., and Zhang, W., Industrialisation, Ecologicalisation and Digitalisation (IED): building a theoretical framework for sustainable development. Industrial Management & Data Systems, 123(4), pp. 1252-1277, 2023. DOI: https://doi.org/10.1108/IMDS-06-2022-0371

[9] Wang, D., Hao, M., Li, N., and Jiang, D., Assessing the impact of armed conflict on the progress of achieving 17 sustainable development goals. IScience, 27(12), art. 111331, 2024. DOI: https://doi.org/10.1016/j.isci.2024.111331

[10] Ren, Y.M., Zhang, Y., Ding, Y., Wang, Y., and Christofides, P.D., Computational fluid dynamics-based in-situ sensor analytics of direct metal laser solidification process using machine learning. Comput Chem Eng, 143, art. 107069, 2020. DOI: https://doi.org/10.1016/j.compchemeng.2020.107069

[11] Aria, M., and Cuccurullo, C., Bibliometrix: an R-tool for comprehensive science mapping analysis. J Informetr, 11(4), pp. 959–75, 2017. DOI: https://doi.org/10.1016/j.joi.2017.08.007

[12] Adadi, A., and Berrada, M., Peeking inside the Black-Box: a survey on Explainable Artificial Intelligence (XAI). IEEE Access, 6, pp. 52138–60, 2018. DOI: https://doi.org/10.1109/ACCESS.2018.2870052

[13] Dwivedi, Y.K., Hughes, L., Ismagilova, E., et al, Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. Int J Inf Manage, 57, art. 101994, 2021. DOI: https://doi.org/10.1016/j.ijinfomgt.2019.08.002

[14] Yang, L., and Shami, A., On hyperparameter optimization of machine learning algorithms: theory and practice. Neurocomputing, 415, pp. 295–316, 2020. DOI: https://doi.org/10.1016/j.neucom.2020.07.061

[15] Stamatatos, E., A survey of modern authorship attribution methods. Journal of the American Society for Information Science and Technology, 60(3), pp. 538–56, 2009. DOI: https://doi.org/10.1002/asi.21001

[16] Qin, S.J., Survey on data-driven industrial process monitoring and diagnosis. Annu Rev Control, 36(2), pp. 220–34, 2012. DOI: https://doi.org/10.1016/j.arcontrol.2012.09.004

[17] Fuller, A., Fan, Z., Day, C., and Barlow, C., Digital Twin: Enabling technologies, challenges and open research. IEEE Access, 8, pp. 108952–108971, 2020. DOI: https://doi.org/10.1109/ACCESS.2020.2998358

[18] Blank, J., and Deb, K., Pymoo: multi-objective optimization in Python. IEEE Access, 8, pp. 89497–509, 2020. DOI: https://doi.org/10.1109/ACCESS.2020.2990567

[19] Lu, Y., Huang, X., Dai, Y., Maharjan, S., and Zhang, Y., Blockchain and federated learning for privacy-preserved data sharing in industrial IoT. IEEE Trans Industr Inform, 16(6), pp. 4177–4186, 2020. DOI: https://doi.org/10.1109/TII.2019.2942190

[20] Wang, J., Ma, Y., Zhang, L., Gao, R.X., and Wu, D., Deep learning for smart manufacturing: methods and applications. J Manuf Syst, 48, pp. 144–156, 2018. DOI: https://doi.org/10.1016/j.jmsy.2018.01.003

[21] Zhang, W., Li, C., Peng, G., Chen, Y., and Zhang, Z., A deep convolutional neural network with new training methods for bearing fault diagnosis under noisy environment and different working load. Mech Syst Signal Process, 100, pp. 439–453, 2018. DOI: https://doi.org/10.1016/j.ymssp.2017.06.022

[22] Lee, K.M., Yoo, J., Kim, S.W., Lee, J.H., and Hong, J., Autonomic machine learning platform. Int J Inf Manage, 49, pp. 491–501, 2019. DOI: https://doi.org/10.1016/j.ijinfomgt.2019.07.003

[23] Din, I.U., Guizani, M., Rodrigues, J.J.P.C., Hassan, S., and Korotaev, V.V., Machine learning in the internet of things: designed techniques for smart cities. Future Generation Computer Systems, 100, pp. 826–843, 2019. DOI: https://doi.org/10.1016/j.future.2019.04.017

[24] Rajendran, D., Sasilatha, T., Rajendran, S., Selvaraj, S.K., Lacnjevac, C., Prabha, S.S., and Rathish, R.J., Application of machine learning in corrosion inhibition study. Materials Protection, 63(3), pp. 280–290, 2022. DOI: https://doi.org/10.5937/zasmat2203280R

[25] Alsina, E.F., Chica, M., Trawiński, K., and Regattieri, A., On the use of machine learning methods to predict component reliability from data-driven industrial case studies. International Journal of Advanced Manufacturing Technology, 94(5–8), pp. 2419–2433, 2018. DOI: https://doi.org/10.1007/s00170-017-1039-x

[26] Yao, J., Tran, S.N., Sawyer, S., and Garg, S., Machine learning for leaf disease classification: data, techniques and applications. Artif Intell Rev, 56, pp. 3571–3616, 2023. DOI: https://doi.org/10.1007/s10462-023-10610-4

[27] Costa, M.A., Wullt, B., Norrlöf, M., and Gunnarsson, S., Failure detection in robotic arms using statistical modeling, machine learning and hybrid gradient boosting. Measurement (Lond), 146, pp. 425–436, 2019. DOI: https://doi.org/10.1016/j.measurement.2019.06.039

[28] Peng, J., Muhammad, R., Wang, S.L., and Zhong, H.Z., How Machine Learning Accelerates the Development of Quantum Dots?†. Chin J Chem, 39(1), pp. 181–188, 2021. DOI: https://doi.org/10.1002/cjoc.202000393

[29] Siddesh-Padala, V., Gandhi, K., and Pushpalatha, D.V., Machine learning: the new language for applications. IAES International Journal of Artificial Intelligence, 8(4), pp. 411–421, 2019. DOI: http://doi.org/10.11591/ijai.v8.i4.pp411-421

[30] Morin, M., Gaudreault, J., Brotherton, E., Paradis, F., Rolland, A., Wery, J., and Laviolette, F., Machine learning-based models of sawmills for better wood allocation planning. Int J Prod Econ, 222, 2020. DOI: https://doi.org/10.1016/j.ijpe.2019.09.029

[31] Jaber, M.M., Ali, M.H., Abd, S.K., Jassim, M.M., Alkhayyat, A., Kadhim, E.H., Alkhuwaylidee, A.R., and Alyousif, S., AHI: a hybrid machine learning model for complex industrial information systems. J Comb Optim, 45(2), 2023. DOI: https://doi.org/10.1007/s10878-023-00988-w

[32] Boutilier, J.J., and Chan, T.C.Y., Introducing and integrating machine learning in an operations research curriculum: an application-driven

course. INFORMS Transactions on Education, 23(2), pp. 64–83, 2022. DOI: https://doi.org/10.1287/ited.2021.0256

[33] Guan, Z., Tian, H., Li, N., Long, J., Zhang, W., and Du, Y., High-accuracy reliability evaluation for the WC–Co-based cemented carbides assisted by machine learning. Ceram Int, 49(1), pp. 613–24, 2023. DOI: https://doi.org/10.1016/j.ceramint.2022.09.030

[34] Saxby, D.J., Killen, B.A., Pizzolato, C., Carty, C.P., Diamond, L.E., Modenese, L., Fernandez, J., Davico, G., Barzan, M., Lenton, G., da Luz, S.B., Suwarganda, E., Devaprakash, D., Korhonen, R.K., Alderson, J.A., Besier, T.F., Barrett, R.S., and Lloyd, D.G., Machine learning methods to support personalized neuromusculoskeletal modelling. Biomech Model Mechanobiol, 19(4), pp. 1169–1185, 2020. DOI: https://doi.org/10.1007/s10237-020-01367-8

[35] Kim, J., Kim, H., and Geum, Y., How to succeed in the market? Predicting startup success using a machine learning approach. Technol Forecast Soc Change, 193, art. 122614, 2023. DOI: https://doi.org/10.1016/j.techfore.2023.122614

[36] Greif, L., Röckel, F., Kimmig, A., and Ovtcharova, J., A systematic review of current AI techniques used in the context of the SDGs. Int J Environ Res, 19, art. 1, 2025. DOI: https://doi.org/10.1007/s41742-024-00668-5

[37] Barua, A., Ahmed, M.U., and Begum, S., A Systematic literature review on multimodal machine learning: applications, challenges, Gaps and Future Directions. IEEE Access, pp. 14804–14831, 2023. DOI: https://doi.org/10.1109/ACCESS.2023.3243854

[38] Weinzierl, S., Zilker, S., Dunzer, S., and Matzner, M., Machine learning in business process management: a systematic literature review, 2024

[39] Jiang, W., and Luo, J., Graph neural network for traffic forecasting: a survey. Expert Syst Appl, 207, art. 117921, 2022. DOI: https://doi.org/10.1016/j.eswa.2022.117921

[40] Jiang, W., Applications of deep learning in stock market prediction: Recent progress. Expert Syst Appl, 184, art. 115537, 2021. DOI: https://doi.org/10.1016/j.eswa.2021.115537

[41] Jiang, W. Graph-based deep learning for communication networks: a survey. Comput Commun, 185, pp. 40–54, 2022. DOI: https://doi.org/10.1016/j.comcom.2021.12.015

[42] Purwono., Ma'arif, A., Rahmaniar, W., Fathurrahman, H.I.K., Frisky, A.Z.K., and Haq, Q.M.U., Understanding of Convolutional Neural Network (CNN): a review. International Journal of Robotics and Control Systems, 2(4), pp. 739–748, 2022. DOI: https://doi.org/10.31763/ijrcs.v2i4.888

[43] Pérez-Cubero, E., and Poler, R., Aplicación de algoritmos de aprendizaje automático a la programación de órdenes de producción en talleres de trabajo: una revisión de la literatura reciente. Direccion y Organizacion, pp. 82–94, 2020. DOI: https://doi.org/10.37610/dyo.v0i72.588

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