PATENT ANALYSIS IN THE REALM OF MACHINE LEARNING IN MANUFACTURING

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Abstract

Patent analysis reveals a surge in machine learning for manufacturing since 1980, hinting at its potential beyond traditional applications. This study explores this trend through three key questions: how machine learning use is evolving, what technological areas patents cover, and where these machine learning applications are being developed. The analysis finds machine learning impacting areas like medical devices and quality control across various industries. These findings suggest that machine learning can improve efficiency, ensure quality, and drive innovation, paving the way for future research into specific applications, productivity impacts, and potential challenges. Patent data from Lens.org was visualized employing of BibExcel, Pajek and VOSviewer.

Keywords: Machine Learning, Manufacturing, Smart Manufacturing, Patent Analysis, Industry 4.0

JEL Codes: D20, D23, D29

İMALATTA MAKİNE ÖĞRENMESİ ALANINDA PATENT ANALİZİ

Öz

Patent analizi, 1980'den bu yana üretim için makine öğrenmesinde bir artış olduğunu ortaya koymaktadır ve geleneksel uygulamaların ötesindeki potansiyeline işaret etmektedir. Bu çalışma bu eğilimi üç temel soru aracılığıyla araştırmaktadır: Makine öğrenmesi kullanımının nasıl geliştiği, patentlerin hangi teknolojik alanları kapsadığı ve bu makine öğrenimi uygulamalarının nerede geliştirildiği. Analiz, makine öğrenmesinin çeşitli endüstrilerde tıbbi cihazlar ve kalite kontrol gibi alanları etkilediğini ortaya koymaktadır. Bu bulgular, makine öğrenmesinin verimliliği artırabileceğini, kaliteyi güvence altına alabileceğini ve yeniliği teşvik ederek belirli uygulamalara, üretkenlik etkilerine ve potansiyel zorluklara yönelik gelecekteki araştırmaların önünü açabileceğini göstermektedir. Lens.org'dan alınan patent verileri BibExcel, Pajek, ve VOSviewer kullanılarak görselleştirilmiştir.

Anahtar Kelimeler: Makine Öğrenmesi, İmalat, Akıllı Üretim, Patent Analizi, Endüstri 4.0

JEL Kodları: D20, D23, D29

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1. Introduction

The growing demand for high-quality, efficient products is forcing manufacturers to adopt new strategies driven by technological advancements. In high-tech manufacturing, even slight variations during production can lead to expensive rework or wasted materials. To ensure quality and stay competitive, companies need detailed information on each product's state throughout the process, including data for making adjustments as needed. Ideally, this data should be analyzed in real time to enable quick actions, like triggering alarms for critical situations. Traditional methods based on cause-effect relationships need to be revised with the increasing complexity of modern manufacturing. New approaches, like machine learning, are needed to handle this complexity and generate actionable insights efficiently. This can lead to improvements in efficiency, quality, and innovation (Wuest et al., 2014: 2016).

The manufacturing industry is drowning in data. From sensor readings on production lines to environmental monitors and machine details, data is exploding. This trend has different names in different countries, like Germany's “Industrie 4.0” or the US’s “Smart Manufacturing”. This data deluge, often called "Big Data," holds immense potential for improving products and processes, especially quality. However, there's a catch: too much data can be overwhelming. It can cloud important issues, leading to delayed or wrong decisions. The industry needs help to harness this data effectively to improve product quality, optimize costs, streamline processes, and gain valuable customer insights. Managing this massive, complex, and ever-changing data landscape is a challenge that demands innovative solutions (Wuest et al., 2016).

Breakthroughs in math and computer science, like statistical learning, along with free and accessible software tools, offer a revolutionary way for manufacturers to manage their ever-growing data lakes. Machine learning, in particular, shows immense promise. However, the vast array of machine learning algorithms, theories, and methods can take time and effort for manufacturing professionals seeking to leverage these powerful tools. This complexity might prevent them from fully utilizing the data riches at their disposal. Studies by McKinsey report that a staggering 40% of the potential value from data analytics today comes from artificial intelligence and machine learning techniques, with machine learning alone contributing between $3.5 trillion and $5.8 trillion annually. The challenge lies in making these powerful tools accessible and user-friendly for manufacturers to unlock the true value hidden within their data (Wuest et al., 2016; Rai et al., 2021).

Machine learning, a powerful tool within artificial intelligence, can automatically learn from data. Unlike traditional programming, it can make decisions and predictions without explicit instructions. This has made it a hot topic in research across many fields, from medicine and material science to manufacturing, self-driving cars, and even understanding human language. There are different flavors of machine learning, like supervised, unsupervised, and reinforcement learning. All these techniques hold immense promise for smart manufacturing. They can automate the collection of valuable insights from data, uncover hidden patterns in production processes, and provide real-time recommendations for better decision-making. In practice, machine learning is being used for predictive maintenance, optimizing processes, scheduling tasks, improving quality control, managing supply chains, and even implementing sustainable practices across various manufacturing sectors (Wang et al. 2020, Meng et al. 2020, Pham & Afify, 2005, Rai et al., 2021).

Machine learning began making strides in manufacturing about two decades ago, addressing production challenges by leveraging dependable training data to acquire knowledge. These trained models proficiently predict outcomes, optimize processing parameters, and concurrently analyze in situ data for real-time defect detection. Recent literature outlines diverse machine learning applications in manufacturing, encompassing tasks like managing geometric deviations, cost estimation, quality assessment, and more. Machine learning’s role revolves around manipulating data, proving integral to Industry 4.0. This technology aids in creating intelligent systems for tasks such as scheduling production lines, planning machine maintenance, predicting machinery failures, monitoring energy consumption, assessing product quality, and detecting manufacturing defects, ultimately enhancing the efficiency and effectiveness of manufacturing processes (Meng et al., 2020, Dogan & Birant, 2021).

Machine learning is a game-changer for manufacturing, with techniques like deep learning, ensemble learning, and linkage learning making a big impact. From cars and clothes to semiconductors and beyond, it's useful across many manufacturing sectors and even in scientific and engineering fields. Most machine learning research focuses on classification, which is basically sorting things into predefined categories. However some manufacturing problems involve clustering, where the goal is to group similar objects automatically, without pre-defined categories. This can be useful for identifying patterns or anomalies in data Dogan & Birant (2021).

Machine learning can be broken down into three main categories: supervised learning, unsupervised learning, and reinforcement learning. These categories help us organize and understand the different algorithms used in machine learning. Supervised learning is a type of machine learning where a computer program is trained on examples. These examples, like recipes with ingredients and results, show the program the relationship between inputs and desired outputs. Once the program is trained, it can be used to predict what the output will be for completely new inputs it hasn't seen before. For example, in 3D printing (additive manufacturing), a supervised learning system could be trained on data sets that show how different printing settings (like temperature, layer thickness, and speed) affect the final surface roughness of the printed part. Once trained, the system could then predict the surface roughness for entirely new printing settings. Unsupervised learning is another kind of machine learning but without pre-labeled data. Imagine sorting a pile of objects without any instructions. That's unsupervised learning! The computer program figures out how to group similar things on its own, like finding patterns or hidden categories in the data. Reinforcement learning is a different approach. Here, the program interacts with an environment and learns by trial and error. It gets rewarded for good decisions and penalized for bad ones. Like training a dog with treats, the program learns what works best to achieve a goal. In 3D printing, reinforcement learning could be used to find the most efficient path for the printer nozzle to move, minimizing printing time or material waste (Jiang, 2023).

This study focuses on how machine learning is being used in manufacturing based on patent trends. The researchers want to give a clear picture of where machine learning has been, where it is now, and where it might be headed in the future for manufacturing applications. To achieve this, they'll be looking at the following questions:

RQ1: How has the trend in the number of patents evolved over the years?

RQ2: What are the key concepts associated with patents in the field of machine learning applied to manufacturing?

RQ3: Which sectors do the patents in the field of machine learning in manufacturing address?

We have analyzed patents from Lens.org between the years 1980 and 2023. “Machine learning” + manufacturing are used as query words.

The paper is organized as follows: First, an introduction gets you started. Then, section 2 dives into what other researchers have written on the topic (literature review). Section 3 explains how the researchers analyzed patents (methodology) and presents what they found in their patent analysis. Finally, the last section wraps everything up with conclusions and ideas for future research.

2. Literature Review

Chua et al (20224) review methods for assessing the quality of metal components produced using Powder Bed Fusion (PBF) Additive Manufacturing (AM). Flawless component integrity is crucial for demanding applications, and ensuring quality remains a challenge. The review focuses on two main categories: (1) In-process quality assessment. (2) Post-process quality assessment.

A recent study by Zhu et al. (2024) explored the exciting world of 3D printing aluminum alloys. Their review dives into four key areas: (1) Different 3D printing methods used for aluminum, like laser powder bed fusion and electron beam powder bed fusion. (2) The special properties and microscopic structures of aluminum alloys and aluminum matrix composites made with these techniques. (3) The pros and cons of each 3D printing method for aluminum. (4) Since laser powder bed fusion is a leading method for aluminum 3D printing, the researchers take a closer look at how factors like heat treatment after printing, powder characteristics, oxidation, and even metal evaporation during printing can affect the final properties and structure of the components.

A new study by Tauhid et al. (2023) tackles a critical issue: protecting intellectual property (IP) in the world of hardware and software. Here's what they explore: (1) The current state of intellectual property rights and the latest developments in IP protection research. (2) There are ways someone might try to steal intellectual property, along with techniques to defend against these attacks. This includes protection for both hardware and software. (3) How IP protection is applied in various situations. (4) The challenges we still face in keeping intellectual property secure and promising areas for future research in hardware and software IP security.

A new study by Mousavizadegan et al. (2023) examines how machine learning is revolutionizing the development of sensors that use light (luminescent sensors). The researchers analyze recent studies on creating these special light-emitting nanomaterials and explore how machine learning can be used to improve these sensors in three ways: (1) Electrochemiluminescence: This type of sensor uses electrical signals to create light. Machine learning is helping to improve these sensors. (2) Fluorescence: This type of sensor absorbs light and then emits light of a different wavelength. Machine learning is being used to make these sensors more sensitive. (3) Chemi/Bio-luminescent sensors: These sensors use chemical or biological reactions to create light. Machine learning is helping to make these sensors more selective, meaning they can detect specific targets more accurately. Overall, the review highlights how machine learning can significantly improve the performance of luminescent sensors, paving the way for exciting advancements in this field.

Iftikhar et al. (2023) conducted a study on artificial intelligence and machine learning in fog/edge computing, specifically focusing on resource management. They analyzed research using a systematic review method to understand how these techniques are being used. Their study covers three key areas: (1) The Current Landscape: They provide background information on AI/ML in fog/edge computing and how it's currently being used. (2) Organizing the Techniques: The researchers propose a classification system (taxonomy) to categorize different AI/ML resource management techniques for fog/edge computing. (3) Comparing Techniques: They compare existing techniques based on their proposed classification system, helping to understand the strengths and weaknesses of different approaches. (4) Future Directions: Finally, they identify challenges that still need to be addressed and suggest promising areas for future research in this field.

Thangavel et al. (2024) explore how artificial intelligence can be used in future satellite networks for communication, navigation, and imaging. They also discuss the challenges of using artificial intelligence in space, like making sure the systems are safe and reliable, and the legal issues that need to be considered. Overall, artificial intelligence is a promising technology for building smarter, more independent satellites that can handle the busy space environment.

Usman et al. (2024) highlight the urgent need for sustainable alternatives to fossil fuels due to their depletion and environmental impact. Biocrude derived from biomass is a promising solution, and hydrothermal liquefaction is a key technology that can create it. This process can convert a wide variety of biomass and even waste materials into bio crude with yields of up to 86%! The study focuses on how hydrothermal liquefaction can efficiently handle different types of biomass and waste. It also explores the role of catalysts in improving the process and the potential for scaling up this technology for large-scale production. The authors even discuss the possibility of continuous operation with water recycling and using machine learning to optimize the process for better efficiency and higher quality biocrude output.

Qureshi et al. (2023) explore how cutting-edge artificial intelligence methods like graph neural networks and reinforcement learning can further improve drug discovery. The article highlights the rise of artificial intelligence-powered startups in biotechnology and drug design, suggesting a future where artificial intelligence will play a major role in bringing new drugs to patients faster.

Industry 4.0 focused on automation and efficiency, but there's a new wave on the horizon: Industry 5.0. This next phase prioritizes sustainability, people, and adaptability. A key concept in Industry 5.0 is human-centric smart manufacturing. Here, human strengths like problem-solving and flexibility are combined with the precision and power of machines and advanced technologies. This creates a super-smart manufacturing system that's not only efficient but also adaptable and sustainable.

Zhang et al. (2023) delve into this concept. They define human-centric smart manufacturing, explore how it's currently being designed, and identify key technologies from Industry 4.0 that are crucial for making it work. They even discuss how this approach will change the way products are manufactured throughout their entire lifecycle, from design to disposal. Overall, their study highlights human-centric smart manufacturing as a critical concept for Industry 5.0, emphasizing the importance of designing systems that put people first to create a sustainable and adaptable future for manufacturing.

Xie, et al. (2023) state that finding new materials with amazing properties is tough, and traditional methods could be faster. This article explores a new approach: autonomous experimental platforms. This review covers (1) how to develop machine learning algorithms for materials science, (2) recent advancements in automated synthesis and data analysis, and (3) challenges and opportunities in building even better autonomous experimental platforms. Overall, autonomous experimental platforms represent a groundbreaking approach to material development, offering researchers a powerful tool to speed up the discovery of next-generation materials.

Hussin et al. (2023) address climate change and the fight against it using carbon capture technology. This technology captures carbon dioxide (CO2) emissions, a major contributor to global warming. Machine learning, a powerful tool for analyzing large datasets, can be used to optimize these capture processes. This can lead to faster development of new technologies and more cost-effective solutions. The researchers conducted a systematic review to analyze research trends in using machine learning for carbon capture. They looked at factors like the number of publications and citations and which countries are leading the research efforts. Overall, their study highlights machine learning as a powerful tool for developing new and improved carbon capture technologies, which are crucial for tackling climate change.

Kilic et al. (2023) state that lithium-ion batteries power many devices, but they have limitations and that researchers are exploring new battery technologies - “beyond lithium-ion batteries” - to overcome these limitations. The focus of the article is finding better materials and designs for lithium-ion batteries. Here's where Machine Learning comes in. The role of machine learning is as follows: (1) Analyze large amounts of data to identify promising materials and design parameters. (2) Speed up the development process by predicting battery performance. Overall, this article highlights the potential of machine learning to revolutionize lithium-ion batteries technology. By effectively using data and sharing knowledge, researchers can develop new, high-performance batteries for the future.

Lithium-ion batteries are everywhere, but they could be better. Kilic et al. (2023) explore "beyond lithium-ion" battery technologies, searching for better materials and designs. This is where machine learning steps in as a game-changer. Here's how: (1) Machine learning can analyze massive datasets to identify promising materials and design features for these new batteries. (2) It can predict battery performance, speeding up the entire development process. Overall, the study highlights machine learning's potential to revolutionize battery technology. By effectively using data and sharing knowledge, researchers can develop next-generation batteries with superior performance.

A new review by Tamir et al. (2023) dives into 3D printing, also known as additive manufacturing, and its growing role in smart manufacturing (Industry 4.0). The focus? How to make 3D printing even better, more reliable, and more efficient. The article breaks down the typical 3D printing process step-by-step, explains different 3D printing technologies and how they work, and explores both traditional and robot-assisted 3D printing setups. But that's not all! They also delve into methods for catching defects, diagnosing problems, and controlling the entire 3D printing process. Here are some key takeaways: (1) Robots can significantly improve 3D printing's reliability and production output when integrated into the process. (2) Combining machine learning with traditional control algorithms is a promising approach for what's called "closed-loop control" in 3D printing, leading to more consistent and precise printing. The article wraps up by discussing the challenges 3D printing faces and what future trends we can expect to see in this exciting technology.

Shah et al. (2024) state that zinc-based batteries offer several advantages, including safety, abundance, and high capacities. This review highlights MXenes, a new class of 2D materials, as a promising electrode material for these batteries. MXenes boast unique properties like thermal/chemical stability, good conductivity, flexibility, and interesting structures, making them ideal for battery applications. The article explores the recent advancements in designing and creating MXenes specifically for use as electrodes in zinc-based rechargeable batteries. The potential of machine learning in optimizing MXene synthesis for better performance is addressed. This article positions MXenes as a promising material for zinc-based batteries, emphasizing recent advancements and future directions for targeted material design.

Zeba et al. (2021) explore the growing role of artificial intelligence in modern manufacturing, particularly within the framework of Industry 4.0, the era of smart and interconnected factories. They focus on analyzing the research trends in artificial intelligence for manufacturing using scholarly literature from 1979 to 2019 and compare research focus before and after the coining of the term “Industry 4.0” (around 2011). The key finding of the article is that the use of artificial intelligence in manufacturing research has significantly increased since the rise of Industry 4.0. This study highlights the increasing importance of artificial intelligence in modern manufacturing, with a focus on recent advancements in areas like smart systems, big data analysis, and real-time optimization.

There's a big push for sustainable, modern building methods driven by a focus on the environment, new energy sources, and even lifestyle changes due to the pandemic. The study by Sánchez-Garrido et al. (2023) explores these modern methods, which use advanced technology to create smart buildings as an alternative to traditional construction. Since we’re in the era of smart manufacturing (Industry 4.0), it's important to understand how these modern construction methods fit in. The researchers found that a major area of focus is integrating these modern methods with the tools and technologies of Construction 4.0, along with improved management practices in the construction industry overall. However, the study also highlights some key gaps in current research. There’s not enough focus on using modern methods for building retrofits (upgrading existing buildings) or on incorporating regenerative design principles (where buildings have a positive environmental impact). This study provides a valuable analysis of current research on modern building methods by combining traditional and advanced methods. It emphasizes the growing importance of these methods for sustainable construction and identifies areas where future research is needed.

Al-Sakkari et al (2024) state that carbon capture, utilization, and sequestration is a promising technology to capture carbon emissions from industries and power plants, reducing their impact on climate change. However, building large-scale carbon capture, utilization, and sequestration systems that are both effective and affordable is complex. This paper proposes using a powerful artificial Intelligence-based assessment tool to model, simulate, and optimize carbon capture, utilization, and sequestration systems. This tool would combine (1) machine learning: machine learning algorithms can analyze vast amounts of data to identify the most efficient and cost-effective carbon capture, utilization, and sequestration configurations; (2) mechanistic modeling: traditional engineering models can be integrated with machine learning for a more comprehensive analysis. The benefits of artificial intelligence in carbon capture, utilization, and sequestration optimization are as follows: (1) reduced costs: artificial intelligence can help design and operate carbon capture, utilization, and sequestration systems at a lower cost; (2) faster material selection: artificial intelligence can analyze data to identify the best materials for capturing and utilizing CO2 quickly (3) improved process design: artificial intelligence can optimize the design and operation of carbon capture, utilization, and sequestration processes for better efficiency; (4) generalizable knowledge: insights gained from artificial can be applied to future carbon capture, utilization, and sequestration projects, further reducing costs. This paper emphasizes the potential of artificial intelligence to revolutionize carbon capture, utilization, and sequestration technology, making it a more cost-effective and powerful weapon in the fight against climate change.

3. Data Analysis and Results

BibExcel, Pajek and VOSviewer are used as data visualization tools. When the node count is smaller than 500, the Kamada-Kawai algorithm is used; if the network has more than 500 nodes, Fruchterman-Reingold algorithm is used. The lists accompanying graphs are refined by Google’s Gemini.

The Kamada-Kawai algorithm offers a technique for generating visual representations of graphs. This method leverages a spring-based force system, where the forces acting on each vertex are directly proportional to their theoretical distances within the graph structure. The algorithm implements springs connecting all vertex pairs, with the individual spring length determined by the corresponding edge weight. Consequently, edges with higher weights translate to longer springs. While the Kamada-Kawai algorithm exhibits a straightforward implementation, its effectiveness is maximized for graphs characterized by a number of edges that is comparable to the number of vertices. Notably, this method demonstrates particular suitability for visualizing lattice-like network structures Kamada & Kawai (1988).

The Fruchterman-Reingold algorithm belongs to the category of force-directed graph layout algorithms. Its primary aim is to determine the placement of nodes within a graph, striving for edges with relatively equal lengths while ensuring nodes maintain a minimum distance from each other. This approach mimics a physical scenario where nodes act akin to repulsive particles, yet they are interconnected by spring-like forces. The algorithm proceeds through a sequence of steps, progressively adjusting the positions of nodes based on these simulated forces. This iterative procedure persists until reaching an equilibrium state, indicating a layout that meets specific criteria, often centered around minimizing overall system energy or maximizing spatial dispersion among nodes. Given its efficacy, this algorithm is widely employed in visualizing intricate and expansive graph and network structures (Gajdoš et al., 2016).

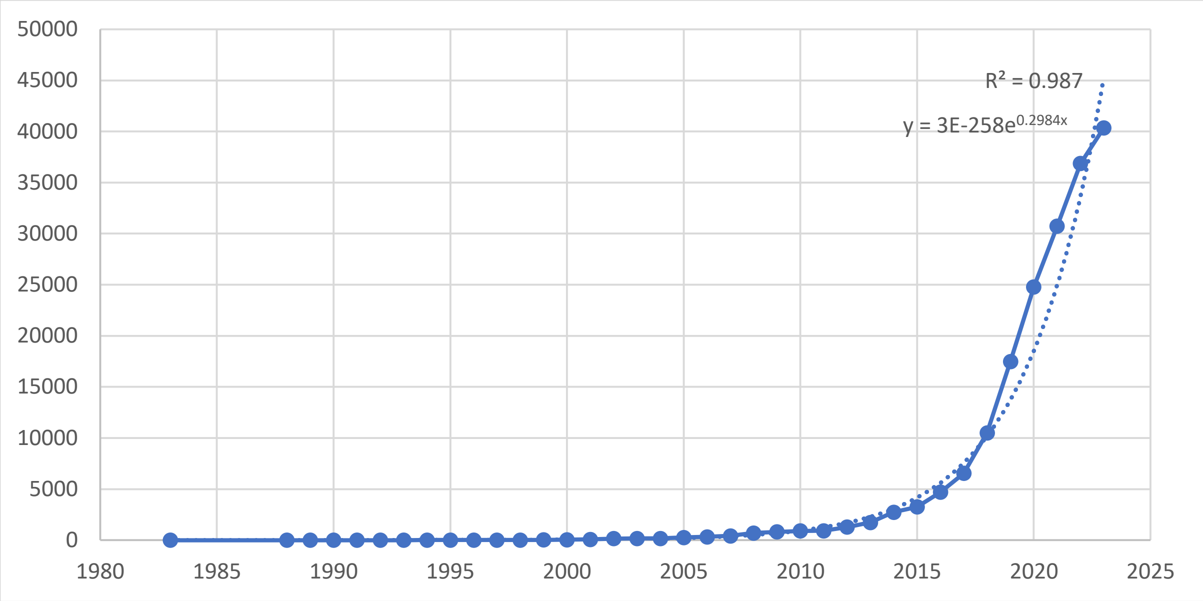
In graph theory, betweenness centrality serves as a metric to quantify the frequency at which a node acts as an intermediary along the shortest paths connecting other nodes within the graph. It represents a normalized measure calculated by determining the total number of shortest paths that pass through each individual node. Consequently, nodes that appear more frequently on these shortest paths will exhibit higher betweenness centrality values White & Borgatti (1994).

Social network analysis utilizes a multi-phase technique known as degree partitioning to dissect a network into distinct communities. This process unfolds in three meticulously executed stages: coarsening, initial partitioning, and partition refinement. The coarsening stage meticulously generates a series of progressively simplified replicas of the original graph, effectively reducing its complexity. Subsequently, partitioning transpires on the most simplified graph, employing recursive bisection techniques to efficiently divide the network into two sub-communities. Finally, refinement is meticulously applied to the original, unaltered graph, leveraging the results gleaned from the preceding stage. This refinement stage ensures the achievement of a desired objective function, optimizing the quality of the partitions (Zhang, et al. 2016).

Analyzing patents is a valuable tool for companies to gain insights into the technology landscape. This knowledge helps them strategically manage the development of their technology, products, or services. By understanding what's already out there, they can make informed decisions about where to invest their R&D efforts and anticipate future market needs Yalcin & Daim (2021).

3.1. Analysis Regarding Patent Quantity Trends

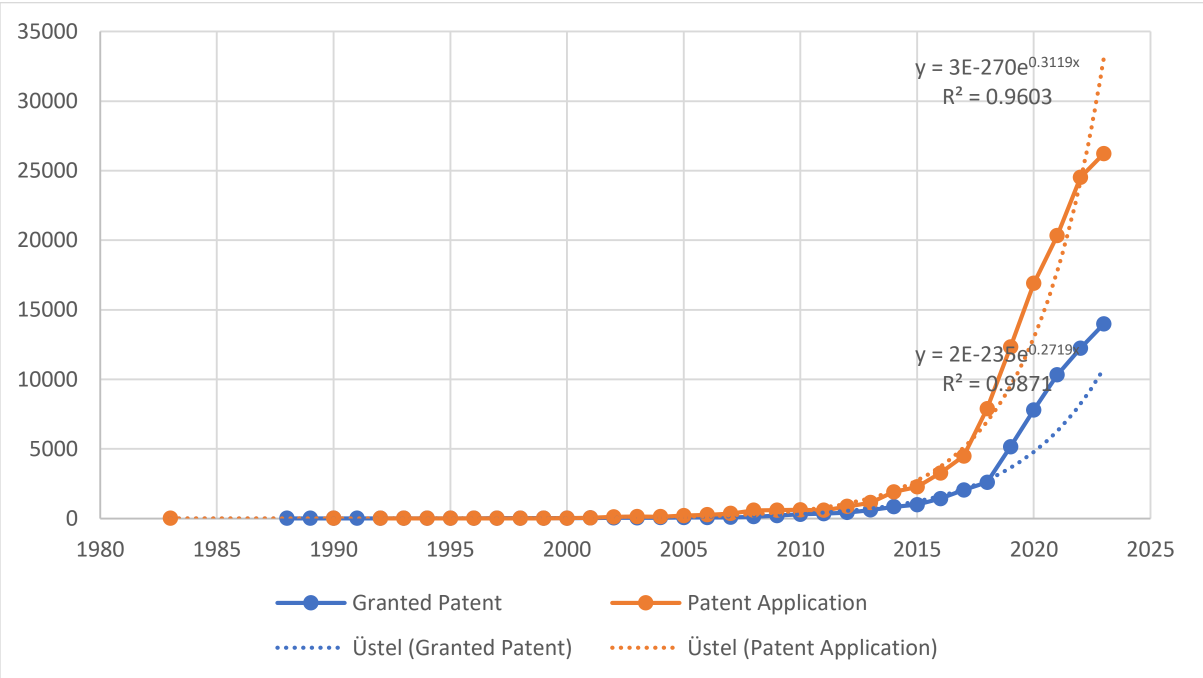
Figure 1. Patent Trend By Years



Patenting activities in the field of machine learning in manufacturing can best be explained by the exponential growth rate ($R^2 = 0.9714$). This means that in the short and middle term, it can be expected that the quantity of patents will continue to increase.

There are no patents obtained in more than one patent office, and this is another fact that shows that machine learning in manufacturing is an emerging field.

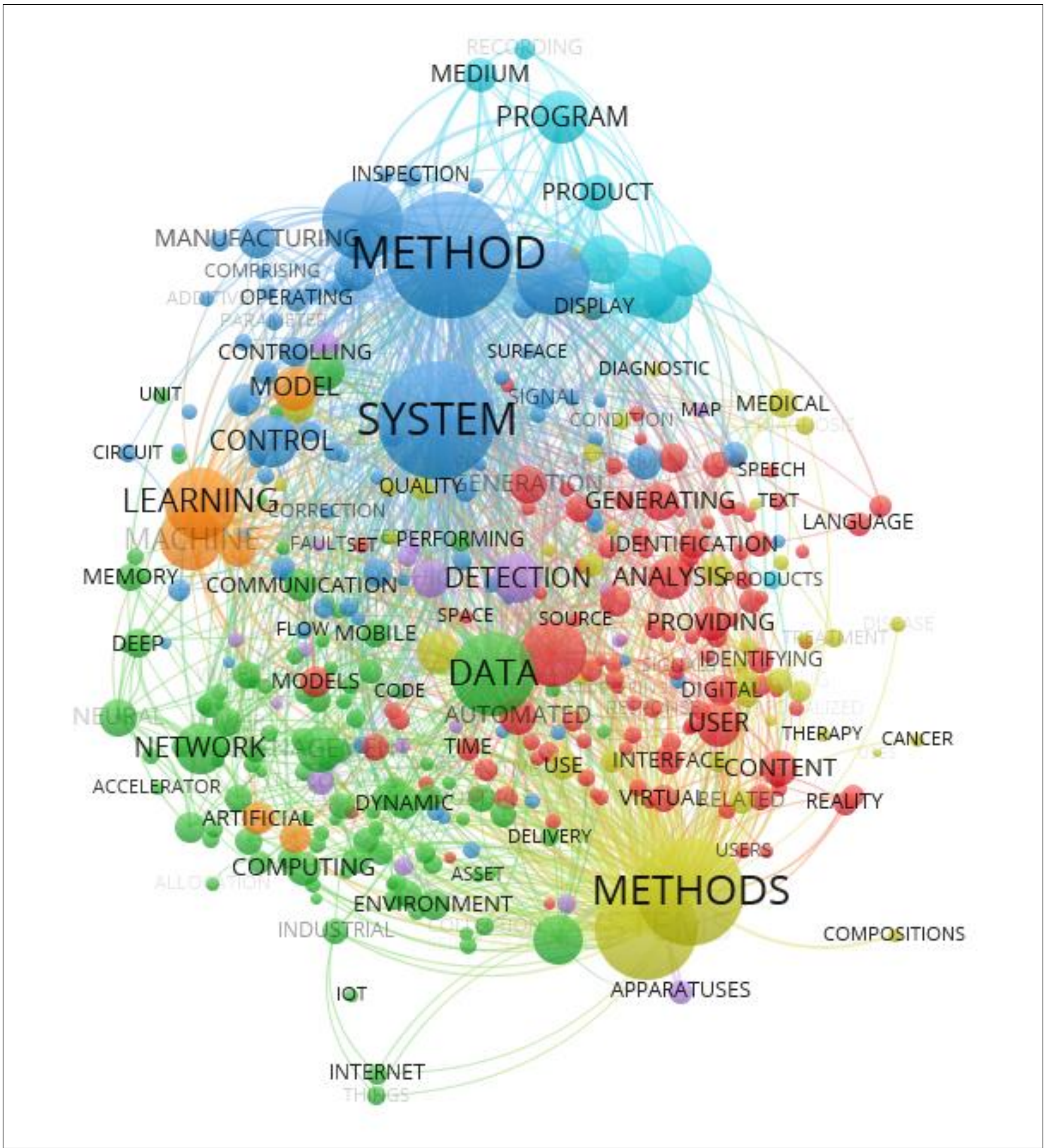
Figure 2. Patent Types by Years



The above graph, with its high R^2 values verifying compliance with the exponential trend line, reinforces the argument that machine learning in manufacturing is an emerging field. The above inferences answer our first research question.

3.2. Patent Keyword Co-occurrence Analysis

Figure 3. Keyword Co-occurrence Analysis (Title Words)



The above Figure, created based on co-word analysis, visualizes the connections and degree of collaboration between keywords determined by artificial intelligence within the scope of patents related to machine learning in manufacturing.

Table 1. The First 20 Words of Keyword Co-occurrence Analysis

Degree	Betweenness Centrality
System	System
Data	Data
Machine learning	Machine learning
Method	Method

Device	Device
Control	Control
Processing	Processing
Detection	Detection
Network	Network
Management	Management
Computer	Computer
Model	Model
Analysis	Analysis
Information	Information
User	User
Interface	Interface
Application	Application
Intelligence	Intelligence
Communication	Communication
Optimization	Optimization

The figure above, along with the corresponding table, illustrates the most commonly utilized keywords within the scope of patents related to machine learning in manufacturing. This addresses our second research inquiry.

3.3. Analysis of Patent CPC Codes

Figure 4. Frequency of Co-occurrence of Patents With Various CPC Codes

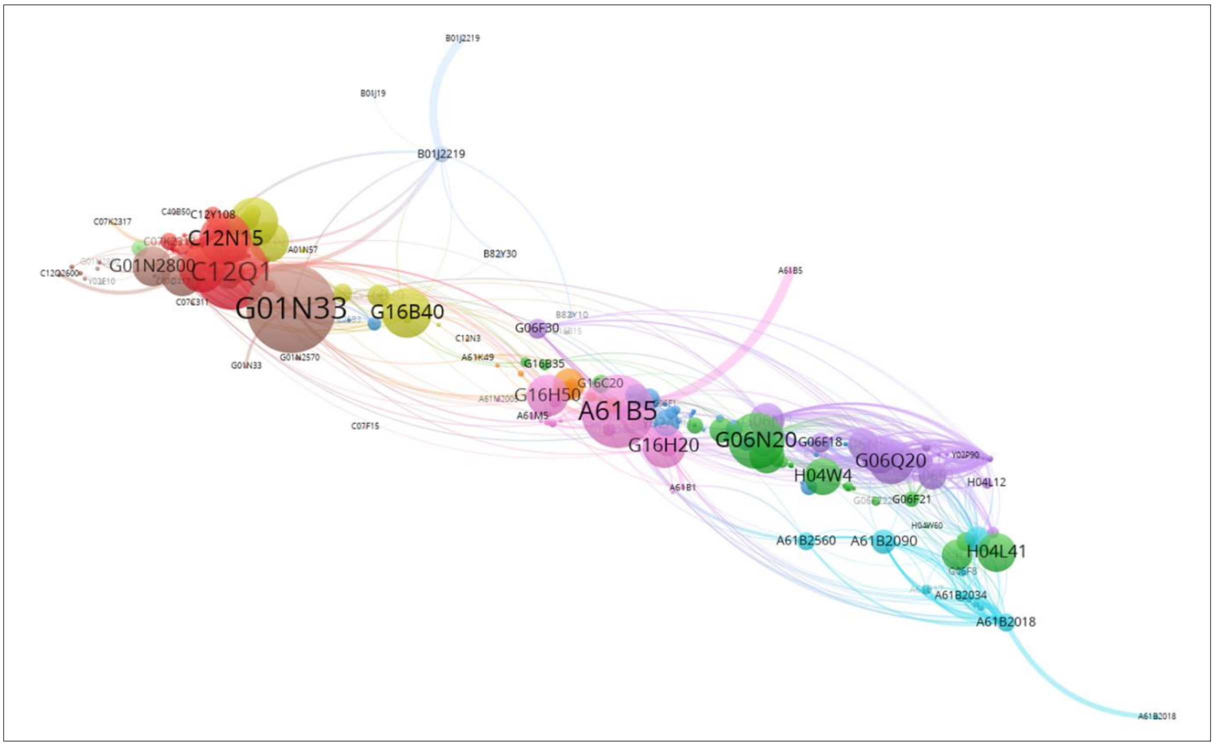


Table 2. The First 25 CPC Codes of Co-occurrence Analysis

All Degree Partition	Betweenness Centrality	Weighted All Degree	High Aggregate Constraints	Low Aggregate Constraints
C12Q1	G01N33	G06Q30	A61K35	G06F13
G01N33	C12Q1	A61B5	G06V20	H03M7
C12N15	A61B5	G06Q20	A61P3	A61B5
A61B5	G06N20	G06N3	A61P31	B01J2219
C12Q2600	C12N15	A61B2018	C12N1	A61B2018
G06N20	G16B40	G06F9	G06T2207	C12Q2600
G06N3	A01N63	G06F16	G06T7	C07K2317
A61P35	A61K31	G06Q10	C07K14	G01N33
C07K14	G06Q20	G06Q50	A61P29	A61K31
A61K31	G16H20	B01J2219	A61P9	G01N2800
G16H20	C12Q2600	C12Q1	A61P13	A61K35
G16B40	C12N9	A61B5	G01N21	B01L2300
G06Q20	G16H50	G01N33	A61P1	G16B30
G01N2800	C12N1	C12Q2600	A61K31	G01N15
G06Q30	G01N2800	A61B2017	C12N2800	G01N21
G16H50	H04L41	G06Q40	C12N15	H04L41
C12N9	G06Q50	B01J2219	A61P43	A61K8
A61P31	H04W4	H02J3	H01L2224	H04W12
G06N5	G06N3	H04L9	G01N33	C12P7
A61K35	G06V20	H04L47	G06F3	G16C20
G06Q50	C07K14	G06N5	A61P37	A61F2002
G16H40	A61P35	A61B2034	A61K48	A01N43
H04L67	G06Q30	H04L67	Y02A50	C07H21
A61K38	G01N21	C07K2317	G01C21	Y10S977
G06N7	G06N5	A61B18	A61K45	C12Y108

The list above depicts the co-occurrence frequencies of patents associated with different CPC codes. To comprehend the pertinent domains, it is essential to provide a general commentary utilizing the explanations of the CPC codes.

The table below lists the patent codes, the frequency of matches between their corresponding patents, and the subjects with which there is a significant patent association.

Table 3. Patent Codes and Frequency of Matches Between Corresponding Patents

Patent Code	Frequency of Matches Between Corresponding Patents	Subjects with Which There Is A Significant Patent Association
A61B5	19106	Medical devices and surgical instruments
B01J2219	13717	Chemical or physical analysis and testing
A61B2018	5394	Medical imaging devices and techniques
G06Q30	3991	Information processing systems and computer methods
G06N3	3023	Machine learning and artificial intelligence
C12Q2600	3130	Methods of measuring biological or chemical processes
G01N33	2035	Analysis and testing
G06Q20	2408	Computer hardware and computer software
G06F16	2941	Computing and digital processing
G06Q10	2145	Finance, business operations and business management
G01N33	2035	Analysis and testing (repeat)
A61B1	2016	Medical devices and surgical instruments (repeat)
A61B2560	1982	Medical devices and surgical instruments (repeat)
G06Q30	1824	Computing systems and computer methods (repeat)
G16H20	1824	Data processing systems and methods
A61K31	1718	Medical and veterinary purposes

The results highlight significant associations between various CPC codes and distinct concurrent patterns among patents. Notably, there is a pronounced patent co-occurrence in diverse areas such as medical devices and surgical instruments (A61B5), chemical or physical analysis and testing (B01J2219), medical imaging devices and techniques (A61B2018), information processing systems and computer methods (G06Q30), machine learning and artificial intelligence (G06N3), and methods for measuring biological or chemical processes (C12Q2600). Furthermore, patent unity is evident in areas such as analysis and testing (G01N33), computer hardware and software (G06Q20), information processing and digital processing (G06F16), finance, business operations, and business management (G06Q10), data processing systems and methods (G16H20), and drugs for medical and veterinary purposes (A61K31). This analysis of patents shows much activity in using machine learning for different parts of manufacturing. This suggests there are many opportunities to develop and improve new machine learning applications in manufacturing. The high number of patents related to machine learning in manufacturing suggests exciting possibilities for innovation and future advancements in this field.

Machine learning can have a significant impact on the manufacturing industry. In this context, analysis of the relationships between specific patent classes reveals potential applications in various technology fields. For example, class C12Q1 includes methods of measuring or determining biochemical processes in the fields of biomedicine and biotechnology. This finding highlights a potential application for machine learning algorithms. They could be used to gain insights into and optimize the intricate biochemical interactions that occur during various manufacturing processes. Class G01N33 includes general methods for the analysis of liquid materials and is important for analytical chemistry and materials science. Application areas of this class include quality control, raw material testing and product characterization. Machine learning can be used in these processes as an effective tool to extract and analyze information from large data sets. Class G06Q30 covers topics such as databases, data mining and big data management for computerized management or business operations. This class is critical for business process management and data analytics. Machine learning, especially data management and analysis in manufacturing processes, can increase efficiency. Class A61K35 contains the patent classification of ingredients used in the making of drugs, dietary supplements, or cosmetic products. Machine learning can be used in this field in areas such as the discovery of new ingredients, formulation optimization and ingredient interaction analysis. Class G06F13 includes methodologies and systems for computer applications. Machine learning can be used in areas such as automation, data analytics and process optimization, especially in manufacturing. Industry 4.0 and smart production concepts are closely related to the technologies in this class. Bringing these five classes together represents various areas of technology and innovation that can be used in a wide range of areas, from biotechnology to pharmaceutical and cosmetics production, from business process management to computer applications. Machine learning in manufacturing holds promise on multiple fronts. By combining different approaches, it can streamline production processes, guarantee consistent quality control, and even pave the way for the development of entirely new products. The above information confidently answers our third research question.

4. Conclusion

This paper has explored the growing significance of machine learning in the manufacturing industry. The analysis of patents revealed a trend of exponential growth in this field, indicating a promising future for machine learning applications in manufacturing.

Key findings include: (1) Rapid growth: as figure 1 and figure 2 indicate the number of patents related to machine learning in manufacturing is rapidly increasing. (2) Diverse applications: machine learning extends its reach beyond conventional manufacturing, finding diverse applications in sectors such as medical devices, pharmaceuticals, and business process management. (3) Data analysis potential: machine learning demonstrates exceptional capabilities in extracting valuable insights from extensive datasets, playing a pivotal role in quality control, process optimization, and fostering innovation within the manufacturing domain.

The convergence of technologies like machine learning with Industry 4.0 concepts holds immense potential for the future of manufacturing.

Future research directions are as follows: (1) Explore the particular applications of machine learning within various sectors of manufacturing. (2) Examine the influence of machine learning on manufacturing by analyzing its effects on productivity, quality, and innovation. (3) Investigate the ethical considerations and potential challenges that arise with the widespread adoption of machine learning in the manufacturing industry.

By delving deeper into these domains, scholars and academics have the opportunity to significantly contribute to the progression of machine learning, thereby enhancing its pivotal role in shaping the future landscape of manufacturing. Simultaneously, industry professionals engaging in comprehensive research and application of machine learning principles can foster innovation, efficiency, and sustainability within the manufacturing sector. As both academia and industry collaborate on exploring these aspects, a synergistic effort emerges to propel the evolution and widespread integration of machine learning technologies in the manufacturing domain.

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