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A Survey of AI Techniques based on Predictive Maintenance in Lean Manufacturing[†]

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Abstract

Predictive maintenance plays a pivotal role in lean manufacturing by helping manufacturers identify and resolve maintenance issues, thereby avoiding expensive downtime or equipment failures. Diverse algorithms have been more prevalent in artificial intelligence and machine learning in recent years, significantly impacting various kinds of industries. This paper surveys the current landscape, focusing on the popularity and effectiveness of different algorithms. Our methodological approach includes a systematic literature review, utilizing a variety of keywords and their synonyms, mainly the Google Scholar Database, for pertinent information. Three tiers of inclusion criteria are further subdivided into the data processing, serving as filters to improve the search results. The information is analyzed, comprising data reduction, descriptive bibliometric analysis, and journal identification that is influential and productive. Our findings highlight that the most widely used algorithm for predictive maintenance in lean manufacturing is a decision tree, which is valuable for both classification and regression tasks across multiple industries. Additionally, convolutional neural networks (CNNs) are noted for their efficacy in pattern recognition within sensor data, aiding in anomaly detection and maintenance forecasting. Another prominent model is artificial neural networks (ANNs), known for their courage in coping with complex problems beyond the scope of conventional methods. However, the popularity of these models raises important questions about their limitations, including overfitting risks and interpretability issues. Examining these details indicates that while certain algorithms are obviously more accurate than others, they can also be perplexing. Therefore, it is suggested that future efforts shift to hybrid models in an effort to achieve a compromise between algorithmic clarity and robust performance. The study concludes by emphasizing the importance of domain-specific evaluations and iterative refinement in models, providing a thorough lens through which experts in machine learning, professionals, and researchers can assess the constantly changing field of artificial intelligence.

Keywords: Predictive maintenance, Artificial intelligence, Lean manufacturing

Introduction

Manufacturing industries have always followed lean manufacturing principles to work efficiently and reduce waste. Lean manufacturing focuses on continuously improving and cutting out unnecessary tasks. At the same time, recent advances in artificial intelligence (AI) offer new tools for analyzing data and predicting issues. Predictive maintenance, as its name suggests, aims to predict when equipment will fail, enabling timely interventions and reducing unplanned downtimes. Traditional maintenance schedules, which are frequently reactive or calendar-based, may cause unexpected equipment failures or early interventions - both of which are incompatible with Lean principles. Integrating AI approaches into predictive maintenance can provide a more expert approach, utilizing vast quantities of data to create precise forecasts and more effectively guide maintenance activities. According to recent research by Antosz et al. (2020), 92 % of senior production managers believe that current "smart factory" technology, such as artificial intelligence, would help them increase productivity and motivate their staff to work smarter. The

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use of AI in manufacturing has the potential to both increase and decrease transformation costs by 20 %, with worker productivity accounting for up to 70 % of the decrease in costs (Panwar et al., 2021).

Many artificial intelligence (AI) approaches are being investigated for their potential in predictive maintenance. For the purpose of developing predictive maintenance solutions, engineers and data scientists have access to a multitude of AI frameworks and libraries. Among the most well-known are scikit-learn, PyTorch, and TensorFlow. These tools include pre-configured models and capabilities that can be tailored to particular industrial settings. An enlarged version of the work on AI for Predictive Maintenance in Industrial Systems is shown in the outline. These methods cover a wide range of techniques, from simpler frameworks like neural networks to more complex algorithms like decision trees (Raza, 2023). This study explores these methods in detail, explaining their advantages, disadvantages, and possible contributions to lean manufacturing. By providing researchers and manufacturing professionals with a thorough guide on using AI for predictive maintenance, we hope to close the current knowledge gap and advance the concepts of lean manufacturing.

Literature review

The subsequent section will provide an overview of prior research on the application of artificial intelligence in the manufacturing sector. Within a production facility, a wide range of lean manufacturing strategies and tools can be applied. Gaining a thorough grasp of the present status of research and development in the field of artificial intelligence (AI) systems for lean manufacturing systems is the aim of the literature review.

Predictive maintenance

Predictive maintenance has become an important aspect of lean manufacturing systems as it helps organizations improve equipment reliability, reduce downtime, and increase overall efficiency. Several manufacturing studies have been carried out to analyze these impacts. For example, several reviews concentrate on the impact of digitalization in the literature. In one of the studies presented by Kamel (2022), he applied artificial intelligence techniques, which are predictive maintenance. Artificial neural networks were used to classify the condition of the machine as failed or operational and concluded that the application of artificial intelligence in the field of maintenance will lead to financial benefits and systems that are more efficient (Ilesanmi et al., 2020). Application of predictive maintenance concepts using artificial intelligence tools, it can be concluded that artificial intelligence tools exhibit enormous potential in the analysis of large amounts of data, thus aiming to improve the availability of systems, reduce maintenance costs, and increase operational performance and support in decision-making (Kamel, 2022). The article on machine learning architecture for predictive maintenance is based on a random forest approach. The system was tested on a real-life industry example by developing the data collection and data system analysis, applying the machine learning approach, and comparing it to the simulation tool analysis. Data has been collected by various sensors, machine PLCs, and communication protocols and made available to data analysis tools on the Azure Cloud architecture. Preliminary results show the proper behavior of the approach for predicting different machine states with high accuracy (Paolanti et al., 2018).

Lean menufacturing

Lean manufacturing focuses on removing non-value-added tasks while increasing value-added activities by lowering costs and enhancing the quality of an organization’s processes. Non-value-added operations typically add costs to the process without increasing its value. In lean manufacturing, non-value-added activities are referred to as waste. Waste can be categorized into 7 areas: Waste due to overproduction, unnecessary waiting, unnecessary transportation, over-processing, excess inventory, unnecessary movement, and defects (George, 2002).

Artificial intelligence (AI) system

Lean manufacturing is well known as an effective means to improve productivity and decrease the costs of operations, using a series of management practices developed first in Japan and then adapted to worldwide circumstances. Rapid technological progress has opened new business potential and opportunities, forcing companies to constantly introduce more and more advanced solutions to remain competitive. However, the potential of such technologies to support the implementation of lean manufacturing is not completely perceived yet (Perico & Mattioli, 2020). The author focuses on the integration and support of AI in lean manufacturing, mainly investigating process and control issues through better use of data and knowledge. So, beyond the sphere of machine-based problems, AI can be valuable to support the competence and knowledge management of employees. The 2 key aspects for the assistance of employees are the guidance of individual learning processes (Ullrich et al., 2015) and the control of competence saturation (Mazziotti et al., 2015) within the production system.

Methodology

This article, based on a literature review, focuses on artificial intelligence, predictive maintenance, and lean manufacturing. This review focuses on combining 3 concepts and creating a comprehensive overview of the studies. This study will propose a hypothesis study based on the following points: “What are the techniques and models in the AI model used for predictive maintenance in lean manufacturing?”

Keywords analysis

This paper reviewed the systematic literature review, which combines various keywords and their synonyms to find quality peer-reviewed journals. (lean manufacturing, artificial intelligence, and predictive maintenance) collect the necessary information from the Google Scholar databases and consider it the appropriate tool to systematically assess and evaluate a given body of literature (Tranfield et al., 2003). Burst detection analysis is based on the analysis of keywords over a certain period of time (Rentsch et al., 2015). The density of the frequency changes of keywords is determined for each monitored period. This analysis helps identify the main research trends and helps predict the future evolution of the literature. The methodology framework for bibliometric analysis and the steps correspond to the methodology and represent the methods or strategies used to perform this study. Furthermore, we analyzed the obtained publications concerning keywords and burst detection. Only the most relevant research publications from the Google Scholar database will be analyzed. Search strategies are shown in **Table 1**.

Table 1 Search strategy for burst detection analysis (2000 - 2023).

Searches	Terms/Keywords
1) Lean Manufacturing/Production	(“manufacturing” OR “lean manufacturing” OR “production”)
2) Artificial Intelligence	(“artificial” OR “intelligence”)
3) Predictive Maintenance	(“maintenance”)
4) AI/Lean Manufacturing	(“lean”, “artificial”)
Query	Operate of (Term1 & Term2 & Term3 & Term4)

Conceptual framework

The process begins with searching for relevant data using specific keywords on a webpage. The primary source of the data is the Google Scholar Database, a reputable academic database. Data processing is further broken down into 3 levels of inclusion criteria, which act as filters to refine the search results. First Level: Filters data based on its publication year (between 2000 and 2022), the type of document, and ensures that the language of the document is in English. Second Level: Narrows down the data based on the subject area, specifically targeting documents related to manufacturing and lean manufacturing, factories, and Industry 4.0. Third Level: Involves more detailed processing like retrieving metadata, creating matrices based on the document and its attributes, and normalizing the data to ensure consistency. After processing, the data undergoes analysis. This includes: Descriptive bibliometric analysis: A statistical approach to analyzing publications Data reduction: Simplifying the data into its most relevant components; identifying productive and impactful journals; recognizing journals that have produced significant and influential research The final step involves presenting the refined and analyzed data visually. Power BI, a data visualization tool, is used to create interactive visual representations of the data. The output is the final data, presented in a comprehensible and accessible manner, as represented in **Figure 1**.

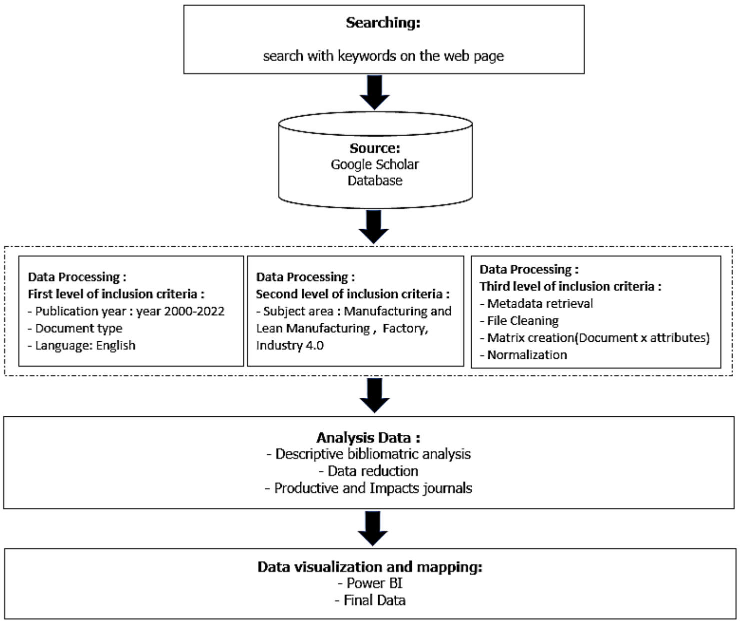

Figure 1 Framework of research that illustrates a structured process from the Google Scholar Database.

Results and discussion

Our research showed an ongoing trend toward the use of AI in modern manufacturing setups, particularly in lean manufacturing environments. Analyzing data from the Google Scholar Database, we observed a surge in publications on this topic between 2010 and 2023. However, while many papers highlighted the transformative potential of AI, challenges such as data normalization and metadata retrieval were frequently cited. Engaging with this synergy between AI and lean manufacturing not only promises efficiency gains but also emphasizes the importance of addressing the associated challenges for optimal outcomes.

Methodologies for predictive maintenance in lean manufacturing

The literature review in **Table 2** consists of papers on applications of methodologies used for predictive maintenance in lean manufacturing. The table provides a comprehensive summary of various research studies from 2015 to 2023, focusing on the application of different machine learning and artificial intelligence algorithms in the field of manufacturing.

Table 2 The summaries encapsulate the core findings or objectives of each study.

Author	Year	Algorithms	Key point
Rentsch et al.	2015	NN, SVR, GBRT, RF	Use a genetic algorithm to optimize energy and resource consumption during shaft manufacturing.
Loyer et al.	2016	Gradient Boosted Trees, Support Vector Regression,	Highlight the cost-effectiveness and scalability of machine learning for early-stage mechanical part design costs.

Author	Year	Algorithms	Key point
		Linear Regression, and Artificial Neural Networks	
Kim et al.	2018	Q-learning, RF, Decision Tree	Introduce a computer simulation scheme that enhances scheduling accuracy and reduces time compared to traditional Q-learning.
Brik et al.	2019	Random Forest	They emphasized the efficiency of their tool for real-time system disruption detection and prediction accuracy.
Garcia et al.	2019	Decision Tree	Employ a decision tree for cost reduction in wind turbine manufacturing.
Merayo et al.	2019	Top-down induction of decision trees	Applied Decision Tree for Optimized Material Selection in Industry 4.0
Pinto et al.	2019	Decision tree, K-Nearest Neighbor, Convolutional Neural Networks (CNNs)	Validate the approach of using multiple algorithms for a service-oriented solution in Comau industrial robots.
Sampaio et al.	2019	Artificial Neural Networks (ANNs)	Demonstrate the potential of neural networks in predicting industrial equipment conditions, aiding smart industry growth.
Tsurumine et al.	2019	Deep P-Network (DPN), Convolutional Neural Networks (CNNs)	Introduce a deep reinforcement learning method for cloth manipulation by dual-arm robots, emphasizing smooth policy updates.
Walther et al.	2019	Gradient Boosting Regression Trees (GBRT)	Establish the feasibility of gradientboosting regression Trees for precise short-term load forecasting.
Zeng et al.	2019	C5.0 algorithm information gain/Decision Tree	Utilize decision tree to understand coal manufacturing regional patterns in China.
Antosz et al.	2020	CART/Decision Tree	Apply decision tree in lean maintenance to reduce operational costs.
Chen et al.	2020	ID3/Decision Tree	Explore the environmental cost control system in manufacturing enterprises.
Kaparthi and Bumblauskas	2020	Conditional inference Tree	Designe predictive maintenance systems to aid decision-making.
Oberc et al.	2020	Neural Network (NN)	Highlighte the impact of AI in learning factories, bridging the gap between blue-collar workers and AI.
Wassouf et al.	2020	DTs, Random Forest, Boosting	Use classification algorithms to increase customer loyalty and revenue.
Ayvaz and Alpay	2021	Correlation Analysis	Focus on maintenance predictions using IoT data for manufacturing tools.
Magalhães	2021	CHAID/Decision Tree	Use the CHAID algorithm for online grocery shopping decision-making.
Huo and Chaudhry	2021	3D vision of mode network, Heat map, Hierarchical cluster analysis	Evaluate global expansion decision impacts in the Chinese manufacturing sector.
Kumar et al.	2021	Keras/TensorFlow	Address energy management in smart factories, predicting energy consumption.
Panjwani et al.	2021	Decision Tree	Predict pathogen safety in biological manufacturing processes.
Qian et al.	2021	CHAID/Decision Tree	Forecast air pollutant emissions and green supply chain management in China.

Author	Year	Algorithms	Key point
Ruschel et al.	2021	Bayesian networks (BN)	Contribute to manufacturing cycle time predictions.
Ying et al.	2021	CNNs, RNN	Propose an integrated management platform for quality control in semiconductor chip production.
Chen et al.	2021	Partial Least Squares Regression (PLSR), Random Forest, Artificial Neural Networks	Design predictive maintenance models for steel production component wear prediction at TATA Steel, Shotton.
Bhatia et al.	2022	Convolutional Neural Networks (CNNs)	Introduce motif discovery approaches for modern manufacturing, achieving higher accuracy with lower computational costs.
Fordal et al.	2023	Artificial Neural Networks (ANN)	Present a predictive maintenance platform using ANNs for Industry 4.0 and sensor-based maintenance.
Pande et al.	2023	Convolutional Neural Network (CNNs)	Develope an AI-powered automated continuous monitoring system to address leakage faults.
Shahin et al.	2023	Convolutional Neural Network (CNNs)	Show how AI technologies ensure adherence to safety practices in the industry.
Shafi et al.	2023	Convolutional Neural Network (CNNs)	Use CNNs for defect detection in aircraft manufacturing, reducing time delays and costs.
Leberruyer et al.	2023	Random forest	Combine AI with quality management for defect prediction and prevention.

The table provides a comprehensive summary of various research studies from 2015 to 2023, focusing on the application of different machine learning and artificial intelligence algorithms in the field of manufacturing. Several key points can be observed:

1) Variety of Algorithms: A diverse range of algorithms, from neural networks (NN) to decision trees and convolutional neural networks (CNNs), have been employed to address various manufacturing challenges. This suggests the adaptability of machine learning techniques to various facets of manufacturing.

2) Application: The table shows the vast applications of AI and ML in manufacturing. For example, Rentsch et al. (2015) used genetic algorithms to optimize energy and resource consumption, while Loyer et al. (2016) employed multiple algorithms to cost mechanical parts during the early design stage. On the other hand, studies by Ying et al. (2021) proposed platforms for lean manufacturing, emphasizing quality management and AI-based defect detection.

3) Decision Trees' Popularity: Decision trees and their variants seem to be one of the most frequently used algorithms. Their application ranges from predicting air pollutant emissions (Qian et al., 2021) to online grocery shopping decision-making (Magalhães, 2021) and pathogen safety evaluation in biological manufacturing processes (Panjwani et al., 2021).

4) Focus on Predictive Maintenance: Several studies, like Fordal et al. (2023) and Chen et al. (2021), focus on predictive maintenance, emphasizing the growing importance of preemptively addressing machinery issues to ensure smooth manufacturing operations.

5) Safety and Quality: Recent studies in 2023, such as Shahin et al., emphasize the integration of AI technologies like computer-based vision to ensure safety protocols, particularly in adhering to safety equipment usage.

In summary, AI and ML are playing an increasingly vital role in modern manufacturing. Their applications range from optimization, cost reduction, predictive maintenance, safety protocols, and quality assurance. The continuous evolution of these technologies and their integration into manufacturing processes underscore their transformative potential in the industry.

The model in the AI techniques used in predictive management

AI models are increasingly being applied in predictive maintenance for manufacturing, using machine learning algorithms to analyze large amounts of data and provide insights into machine health. These models can be used to predict when maintenance is required, identify potential issues before they become critical, and improve overall equipment effectiveness, as shown in **Table 3**.

Table 3 AI techniques used in predictive management for lean manufacturing.

Techniques	Models/Algorithms	References
Machine Learning Techniques	Bayesian Networks	Ruschel et al. (2021)
	Classification/Regression	Ayvaz (2021), Cakir (2021), Kim (2020)
	Decision Tree	Antosz et al. (2020), Chen et al. (2020), Chen et al. (2021), Magalhães (2021), Garcia et al. (2019), Gupta et al. (2022), Kaparthi et al. (2020), Kumar et al. (2021), Merayo et al. (2019), Min et al. (2019), Panjwani et al. (2021), Qian et al. (2022), Singgih et al. (2021), Smith et al. (2022), Yacob et al. (2019), Zangaro et al. (2020), Zeng et al. (2019)
	Gradient Boosting Regression Trees (GBRT)	Walther et al. (2019)
	K-Nearest Neighbor(k-NN)	Altman et al. (1992), Jung et al. (2018)
	Random Forest	Brik et al. (2019), Leberruyer et al. (2023)
	Support Vector Machine (SVM)	Gryllias et al. (2012), Salcedo-Sanz et al. (2014), Vapnik et al. (1999)
Deep Learning Techniques	Artificial Neural Networks (ANNs)	Dröder et al. (2018), Fordal et al. (2023), Königs et al. (2017), Ktari and Mansori (2022). (2020), Li et al. (2020), Repalle et al. (2020), Samnejad et al. (2020), Sampaio et al. (2019), Simon et al. (2020),Yacob et al. (2019)
	Convolutional Neural Networks (CNNs)	Alexopoulos et al. (2020), Alguri et al. (2021), Bhatia et al. (2023), Gaikwad et al. (2020), Kumar et al. (2021), Li et al. (2020), S. Feng et al. (2019), Shafi et al. (2023) , Shahin et al. (2023), Stieber et al. (2020), Su et al. (2021), Wang et al. (2020), Yiping et al. (2021), Zheng et al. (2020), Zotov et al. (2020)
	Neural Networks (NN)	Oberc et al. (2020)
Hybrid Modeling Techniques	SAE, SVM	Long et al. (2020)
	SVM, Naive Bayes	Shakya et al. (2017)
	RF, LSTM	Chiu et al. (2020), Raissi et al. (2018)
	NN, SVR, GBRT, RF	Rentsch et al. (2015)
	GBT, SVR, LR, ANN	Loyer et al. (2016)
	Q-Learning, RF, DTs	Kim et al. (2018)
	DTs, k-NN, CNNs	Pinto et al. (2019)
	DPN, CNNs	Tsurumine et al. (2019)
	CNNs, RNN	Ying et al. (2021)

Techniques	Models/Algorithms	References
	DTs, Random Forest, Boosting	Wassouf et al. (2020)
	DTs, Random Forest, NN	Smith et al. (2022)

In particular, machine learning (ML) and deep learning (DL) techniques have shown great potential for applications in manufacturing. **Figure 2** shows that when applying AI techniques to lean manufacturing, a combination of several models can be used to optimize production processes.

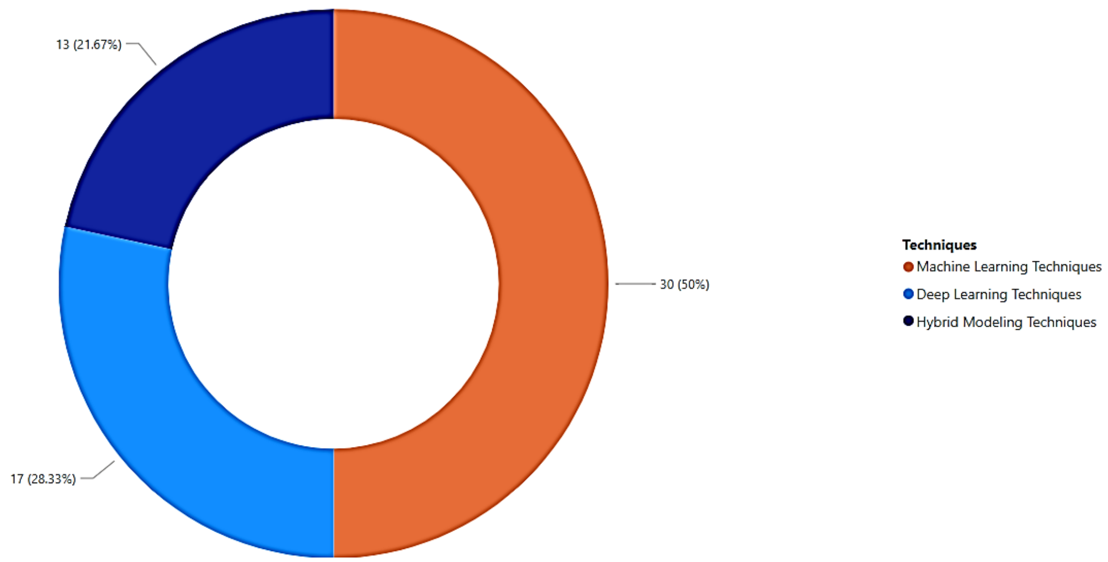

Figure 2 AI techniques in analyzed areas in lean manufacturing.

The given pie chart represents the distribution of different AI techniques used in various studies or applications, as denoted by the number of occurrences. The chart provides a comparative insight into 3 primary techniques: Machine learning techniques, deep learning techniques, and hybrid modeling techniques.

1) Popularity of Deep Learning: Deep learning techniques are the most widely used, covering half of the represented techniques. This suggests a growing trend and confidence in deep learning methods, possibly due to their capabilities for handling large datasets and complex patterns.

2) Machine Learning Still Relevant: Despite the rise of deep learning, traditional machine learning techniques are still prominently used, as evidenced by their 47 % representation. This could indicate that for certain applications or datasets, machine learning methods are more suitable or efficient.

3) Emergence of Hybrid Models: Hybrid modeling techniques account for a third of the total, which is significant. This implies that researchers or professionals are combining the strengths of both traditional machine learning and deep learning to develop more robust and versatile models.

4) Choosing the Right Technique: The distribution reflects that there's no one-size-fits-all in AI. The choice between machine learning, deep learning, or hybrid models depends on the specific problem, dataset size, available computational resources, and desired outcomes.

5) Potential for Future Research: The presence of all 3 techniques indicates a diverse research landscape. There might be potential for further exploring hybrid models, given their intermediate representation, to combine the best of both worlds and tackle complex problems.

Deep learning seems to be leading the charge in recent times, but traditional machine learning and hybrid methods continue to have their unique places and benefits in the AI landscape. This diversity ensures that AI remains adaptable and capable of addressing a wide range of challenges.

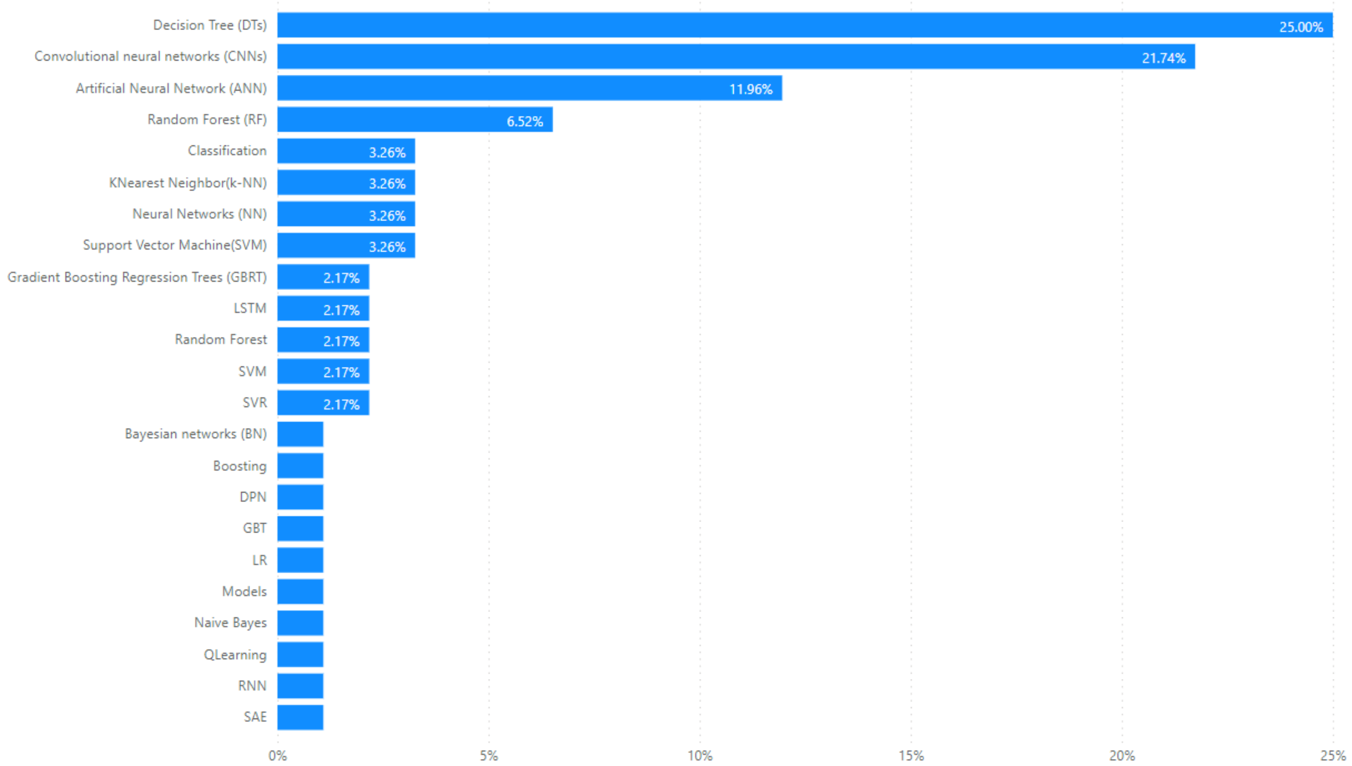

Figure 3 The frequencies of models in analyzed areas in lean manufacturing.

The given bar chart (**Figure 3**) showcases the distribution of various machine learning and deep learning algorithms in terms of their usage or representation, presumably in research studies, projects, or applications. The algorithms are ranked based on their percentage representation.

1) Dominance of Tree-Based Models: Decision trees being at the top indicates their popularity due to their simplicity, interpretability, and effectiveness in various tasks. When combined with ensemble methods like random forest or gradient boosting, they can achieve state-of-the-art results.

2) Rise of Neural Networks: The high representation of CNNs and ANNs signifies the increasing dependency on neural network architectures, especially in tasks that involve large datasets or require capturing intricate patterns.

3) Ensemble and Boosting Techniques: The presence of ensemble methods such as Random Forest, Boosting, and GBRT highlights the industry's inclination towards models that combine multiple algorithms to improve prediction accuracy.

4) Specialized Algorithms: LSTM and RNN's representation indicates their specialized use in sequential data analysis, especially in time series and natural language processing tasks.

5) Balanced AI Ecosystem: The equal representation of several algorithms suggests a balanced AI ecosystem where both classical and modern algorithms have their place, and the choice of algorithm is largely determined by the specific problem at hand.

6) Future Directions: With the diversity of algorithms represented, there's room for hybrid models that combine the strengths of multiple algorithms. As AI continues to evolve, we might witness more integrated approaches that draw from a broader pool of methods to address complex challenges.

The novel findings of this research found that predictive maintenance plays a pivotal role in lean manufacturing by helping manufacturers preemptively identify and resolve maintenance issues, thereby avoiding expensive downtime or equipment failures. This means that predictive maintenance can help manufacturers save time and money by detecting potential issues before they become major problems. By using AI techniques for predictive maintenance, manufacturers can optimize their production processes and reduce the risk of unplanned downtime, which can lead to significant losses in productivity and revenue.

This research could revolve around the potential efficiencies and innovations brought about by hybrid models. Given their significant representation, these models might be at the forefront of addressing complex problems that neither traditional machine learning nor deep learning can solve independently. Additionally, the research might uncover new integrative approaches that combine multiple algorithms in novel ways, setting a precedent for future studies and applications.

In summary, the comparative analysis suggests a dynamic AI research environment where traditional, modern, and hybrid techniques are all critical to the field's progression. Novel findings could influence future research directions, emphasizing the development of hybrid models that harness the collective strengths of various AI techniques.

Conclusions and Limitations

In this research paper, we analyze and focus on techniques and models of AI applied to predictive maintenance in lean manufacturing. The contribution of this paper is to provide a useful basis for the literature search to address "The techniques and models in the AI model used for predictive maintenance in lean manufacturing."

The data reflects the various landscapes of machine learning and AI techniques currently in use. The diversity in the lineup of algorithms, from simple to complex, highlights the adaptability of the AI community in choosing the right tool for the right task, keeping in mind the trade-offs between accuracy, interpretability, and computational costs. However, the presented data comes with its own inherent limitations. The popularity of an algorithm doesn't necessarily translate to its effectiveness in all scenarios. Moreover, this distribution might be influenced by factors such as the ease of implementation, availability of resources, or even current academic and industry trends rather than the pure efficacy of the algorithm. Another crucial aspect to consider is the potential for overfitting with complex models, especially when they are not supplied with sufficiently diverse training data. Furthermore, the chart does not provide context about the kinds of problems these algorithms are being used to solve, leaving a gap in understanding their real-world applicability.

In light of the conclusions and limitations, several avenues for future work emerge. Most importantly, a deeper analysis is warranted to understand the specific domains or industries where each of these models finds its most potent application. By cross-referencing the popularity of an algorithm with its domain-specific successes, we can derive a more suitable understanding of its real-world utility. It would also be beneficial to track the evolution of these preferences over time. As the field of AI and machine learning is dynamic with rapid advancements, understanding the way these algorithms work can offer insights into emerging trends, potential areas of research, and fade-away methodologies. Considering the concerns of overfitting, especially in complex models, future studies could examine best practices for model validation and strategies to ensure generalizability. This would not only optimize the performance of these algorithms but also enhance their trustworthiness in real-world applications.

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