Archives of Computational Methods in Engineering
https://doi.org/10.1007/s11831-025-10290-z

REVIEW

Systematic Review of Artificial Intelligence, Machine Learning, and Deep Learning in Machining Operations: Advancements, Challenges, and Future Directions

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Received: 11 February 2025 / Accepted: 20 April 2025

Abstract
The integration of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) has transformed machining processes, significantly boosting efficiency, accuracy, and sustainability. This systematic review analyzes 182 research articles, categorized into eight thematic clusters using VOSviewer software, based on author keywords from the Scopus database, following the PRISMA framework. These clusters comprise 'advanced sensing and prognostics,' 'machine learning and optimization in manufacturing,' sustainability group ('energy efficiency and optimization techniques', 'smart and sustainable manufacturing', 'neural networks and energy management'), 'intelligent machining processes,' 'advanced algorithms in machining,' 'lubrication and tool wear management,' 'CNC and deep learning applications,' and 'digital twins. A critical literature review of each cluster was conducted to identify key trends, challenges, and developments in AI, ML, and DL applied in machining operations. The vital results are presented in table format. The review reveals that AI-driven machining has significantly enhanced predictive maintenance, real-time process monitoring, and energy optimization, resulting in a reduction of machining energy consumption by up to 20%. ML and DL models have improved machining accuracy, tool wear prediction, and adaptive process control. While progress has been made, difficulties persist in merging AI models with industrial systems. This review also highlights significant research gaps in data quality, system adaptability, and the scalability of AI solutions when integrating AI and ML with practical machining applications. The review addresses these gaps by proposing techniques that improve model accuracy and reliability across various machining contexts and provides a roadmap for future advancements in intelligent manufacturing systems.

1 Introduction

The convergence of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) has revolutionized the sustainable energy sector by enhancing efficiency, optimizing resource utilization, and reducing environmental impact. AI, ML, and DL in machining operations for sustainable energy utilize high-performance computational techniques and technologies to solve complex problems. Machining is a manufacturing process in which raw materials are removed to shape a final product or component, involving cutting, drilling, milling, and turning operations [1]. Machining operations are integral to modern manufacturing, involving industries ranging from automobiles and aerospace to renewable energy sectors. They are resource-intensive, consuming vast amounts of energy and generating waste materials. Research indicates that they consume almost 30% of the energy in manufacturing plants. The average machining process consumes nearly 18–20 kWh

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of energy per kg of material removed, depending on the material and process conditions [2]. Therefore, sustainable manufacturing through eco-friendly machining practices is crucial for achieving low industrial greenhouse gas emissions. Traditionally, machining was either done manually or with primitive automated methods. Computer numerical control (CNC) technology is now widely used, allowing computer-guided machine tools to operate with high precision [3]. CNC technology assures that the machining process produces the precise tolerances, surface finishes, and material qualities required for high-quality manufacturing [4].

Computing in machining represents a transformative leap in manufacturing, enhancing precision, efficiency, and adaptability. AI, ML, and DL in machining have significantly transformed the design, manufacturing, and optimization of components. AI, ML, and DL allow real-time data analysis, predictive modeling, and adaptive control of machining processes, resulting in substantial improvements in precision, efficiency, and resource management [5, 6]. AI-driven algorithms can predict tool wear in real time, allowing the system to make proactive adjustments that increase tool life and machining efficiency [7]. Similarly, ML models may constantly learn from historical data to improve machining processes, resulting in more effective and consistent results. With its ability to analyze large datasets, DL can detect subtle patterns in machining operations, increasing precision and optimizing cutting paths or tool movements. One of the most significant advances enabled by improved computing in machining is the use of digital twins, which are virtual reproductions of actual machines. Manufacturers can enhance productivity, reduce costs, and maintain a competitive edge in a continuously changing market by adding AI, ML, and DL to machining operations [8]. The integration of modern computers and machining has the potential to significantly contribute to global sustainability efforts by reducing material waste, optimizing energy use, and reducing the need for physical prototypes. Combining innovative computational techniques with traditional machining processes enhances production efficiency and quality, aligning with the global push for sustainable energy solutions. Manufacturers can gain both economic and environmental benefits by leveraging AI, ML, and DL capabilities. Figure 1 depicts AI, ML,

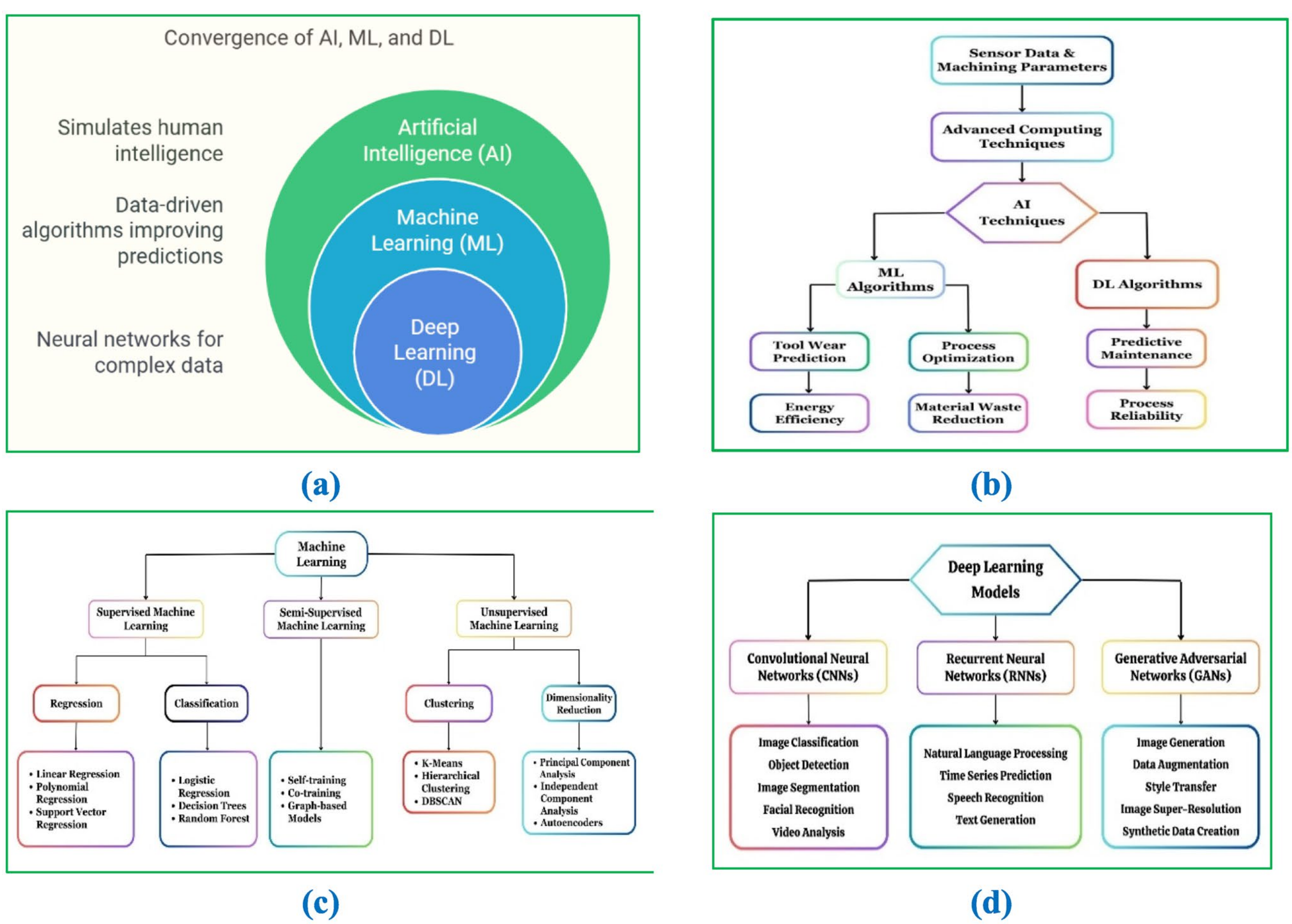


Fig. 1 **a** Convergence of AI, ML and DL, **b** AI techniques, **c** types of ML techniques, **d** DL techniques

and DL machining processes that utilize sensor data and machining settings to enhance operational efficiency and reliability. Figure 1a shows the convergence of AI, ML, and DL; Fig. 1b depicts AI techniques; Fig. 1c shows various ML techniques; and Fig. 1d shows DL techniques. A brief description of ML and DL is given below.

AI has found diverse applications in optimizing machining processes and enhancing industrial sustainability, abrasive water jet machining of carbon fiber-reinforced polymers [9], to reduce thermal deformation in machine-tool spindles, improving precision in manufacturing [10, 11], to detect chatter [12]. AI supported the performance enhancement of electrical discharge machining (EDM) [13]. AI-based process modeling facilitated sustainable machining of Inconel 718 [14]. The design of intelligent simulators using ANN and ANFIS models aided in predicting milling performance and optimizing processes [15]. AI-powered computer vision was integrated into sustainable smart product-service systems [16]. Energy optimization in milling operations for 304L steel was achieved through AI methods [17]. Robust optimization combined with AI helped to design energy-efficient, high-precision multi-pass turning processes [18].

ML is a branch of AI that focuses on creating algorithms and models to allow machines to learn from and make predictions about data [19], refer to Fig. 1c. ML forecasts results, optimizes operations, and reduces waste in machining and sustainable energy solutions [20]. Fawad et al. [21] focused on the role of ML in predictive maintenance, process optimization, quality control, and adaptive manufacturing. The study highlighted how integrating ML with sensor data improved real-time adjustments, reduced downtime, optimized CNC machining, and enhanced defect detection. Kim et al. [22] introduced a data-driven system using ML and metaheuristic algorithms. The system achieved a 77.83% reduction in fault rates and a 17.64% decrease in cycle times to enhance process optimization. In supervised learning, an ML approach, the model learns from labeled input–output pairs using a training dataset where inputs and their corresponding outputs are predefined. In machining, ML algorithms utilize historical data to predict tool wear, surface finish quality, and other key variables [23]. It enables one to preemptively adjust machining parameters, ensuring peak performance while minimizing material waste and energy consumption. Fawad et al. [21] studied the role of ML in predictive maintenance, process optimization, quality control, and adaptive manufacturing. It highlighted how integrating ML with sensor data improved real-time adjustments, reduced downtime, optimized CNC machining, and enhanced defect detection. In unsupervised learning, training models work on unlabelled data to realize structures, correlations, and patterns [24]. Unsupervised learning has applications in manufacturing, including anomaly identification, hidden pattern recognition in process data, and clustering comparable machining operations. Reinforcement learning (RL) is another ML approach in which an agent learns to make decisions by interacting with its environment and receiving feedback through rewards or penalties. RL dynamically adjusts machining parameters in real-time to produce optimal results. RL minimizes energy use and maximizes efficiency, aligning with the goals of sustainable energy solutions.

ML has transformed machining operations by enhancing efficiency, precision, and adaptability. It is used for predictive maintenance to minimize downtime [25], tool wear monitoring to optimize tool life [26], and real-time process control to stabilize operations, prevent defects [27, 28], to monitor tool condition [29]. ML models optimize machining parameters such as cutting speed and feed rate, improving quality, and reducing energy consumption [30, 31]. ML enables defect detection through computer vision [16, 32], machinability analysis for new materials [33, 34], and the development of digital twins for process simulation [35]. Applications such as chatter detection [36–38], energy optimization [39, 40], and custom automation improves productivity [41] and reduce costs [42], making ML a cornerstone of modern manufacturing.

DL, a branch of ML, automatically extracts features from unprocessed data using layered neural networks. Analyzing big datasets and seeing intricate patterns does exceptionally well on tasks like speech recognition and image categorization [43], refer to Fig. 1d. DL provides a new degree of precision and adaptability in machining for sustainable energy solutions, making it an indispensable tool for optimizing complicated manufacturing processes. Neural Networks are the foundation of DL [44]. These computational models are modeled after the human brain's structure, consisting of layers of interconnected nodes (neurons) to process information hierarchically [45]. Neural Networks simulate complex interactions between input factors (cutting speed, feed rate, and material qualities) and output variables in machining. These models learn from previous data to predict results under various settings, enabling real-time adjustments to machining parameters. This capacity improves machining precision while minimizing waste and increasing energy efficiency, harmonizing with the goals of sustainable energy solutions. McDonnell et al. [46] applied neural networks for optimizing and visualizing outcomes in laser surface texturing, significantly reducing experimental data needs and development time while maintaining accuracy.

DL has various applications in machining and manufacturing and was used for sidewall profiling and surface roughness measurement in precision components [47] and energy-efficient milling of CFRP composites through optimization [48–50]. DL aids in phase identification in materials like Ti–6 Al–4 V using X-ray diffraction patterns [32] and CNC machine control using reinforcement learning

[51]. It supports load balancing in virtual machine migrations [52], temperature prediction during rotary ultrasonic bone drilling [53, 54], and energy consumption prediction in machining systems [55, 56]. DL also facilitates workpiece setup optimization in CNC milling [57], multi-pass cutting parameter optimization for aviation parts [40], and milling chatter detection using vibration signals [58]. Additional applications include laser ablation visualization using plasma imaging [59] and machining parameter optimization considering costs [42].

The rapid advancement of AI, ML, DL, and optimization techniques has significantly impacted manufacturing and engineering. Table 1 presents key insights from review papers on AI, ML, DL, and optimization in manufacturing and engineering. However, despite numerous studies exploring AI applications in these domains, a unified and structured understanding of their contributions, challenges, and future potential remains unexplored. Existing research is often scattered, with studies focusing on specific areas, such as machining processes, digital twins, process optimization, and energy efficiency, without a comprehensive synthesis. This lack of consolidation makes it challenging to identify common trends and key challenges that impede the full-scale implementation of AI in smart manufacturing and sustainable energy systems.

A review of existing literature, Table 1, highlights several critical challenges and gaps in AI-driven manufacturing research. The primary concern is the integration of AI and ML in machining and manufacturing processes and energy efficiency of machining operations [60]. AI has been widely applied in surface roughness and quality prediction, tool condition monitoring, parameter optimization, and energy conservation. However, data quality issues, explainability of AI models, and integration with legacy systems still have some challenges. Predictive maintenance, real-time intelligent monitoring, and scalable, computationally efficient, and transferable AI models have not achieved scalability, computational efficiency, or even transferability in AI models. Another key area of concern is AI-driven smart manufacturing and Industry 4.0. Digital Twins (DTs) have emerged as a powerful AI-enabled tool for smart manufacturing and human–robot collaboration. However, their multi-scale integration, sustainability considerations, and automation capabilities require further enhancements. Additionally, AI's role in process optimization and decision-making is expanding; however, technical complexities and compatibility issues with existing systems limit its widespread adoption. Another highly focused area has been energy efficiency and sustainability in machining processes, where AI has been applied to model and optimize energy consumption. Optimization techniques that employ AI have proven effective in achieving up to 20% reduced energy consumption in machining. However, further research is still necessary to develop robust and adaptive strategies that promote efficiency and sustainability. Many AI and ML models suffer from computational limitations, a lack of explainability, and transferability issues, and require further refinement and adaptation to diverse machining scenarios. Similarly, AI applications in robotic precision manufacturing, such as robotic abrasion and force-controlled machining, are still developing. Evaluation metrics and automation frameworks need to be standardized.

Despite these advances, the absence of a comprehensive and structured analysis of AI, ML, and DL in machining and sustainable energy applications presents a significant research review gap. Existing review studies focused on specific applications without a holistic review of trends, challenges, and future research directions. This fragmentation hinders the ability of researchers and industry professionals to identify effective AI strategies for enhancing process efficiency, reducing energy consumption, and improving quality control. For this gap, the present paper formulates the following research question:

> "How can AI, ML, and DL be systematically categorized and critically analyzed in machining operations to provide a holistic understanding of research trends, key challenges, and future directions?"

This research problem aims to conduct a systematic literature review by analyzing 182 research documents related to the application of AI, ML, and DL in manufacturing and energy. The study will categorize these papers according to the selected keywords and provide a critical review of each cluster. This step will help define commonalities, emerging trends, and research gaps within AI-driven manufacturing. Furthermore, the paper will provide fresh insights into sustainability-focused AI applications, aid in bridging the gap between academic research and industrial practice, and outline the following key research objectives.

- To systematically collect and categorize AI, ML, and DL applications in machining by gathering articles from the Scopus database and classifying them into thematic clusters based on author keywords.
- To perform a cluster-wise critical literature review by analyzing each cluster's trends, advancements, key contributions, and challenges.
- To evaluate AI, ML, and DL's role in energy efficiency, sustainability, and process optimization by assessing how models and optimization algorithms reduce energy consumption, improve machining precision, and enhance sustainability in manufacturing.
- To provide future research directions and identify key challenges and research gaps such as data quality issues, model interpretability, and computational efficiency.

Table 1 Key insights from review papers on AI, ML, DL, and optimization in manufacturing and engineering

References	Focus area	Key topics	Challenges and trends	Publication year/citations	Type of review
[61]	ML in machining processes	Roughness quality prediction Tool condition monitoring Energy consumption	High computational demands Focusing on scalability and Algorithm refinement	2021/37	Overview
[62]	AI-driven digital twins in Industry 4.0	AI integration in DTs Smart manufacturing Human–robot interaction	Multi-scale integration of DTs Enhancing AI-driven DTs for sustainability, automation	2021/179	Comprehensive Review
[63]	Natural fiber-reinforced polymer composites (NFRPCs)	AI-enhanced manufacturing systems	Detecting defects and damages efficiently NDE images and AI to develop computational models and improve analysis quality	2022/30	Focused Review
[64]	AI applications in machining operations	Predictive modeling Parameter optimization Chatter stability Tool wear Energy conservation	Data quality, explainability, and transferability of AI models Improving data handling, explainable AI (XAI), and domain adaptation	2022/25	Thematic Review
[65]	Intelligent machine tools in intelligent manufacturing	AI in machining processes Tool condition monitoring	Intelligent machine tools, global market competition, energy efficiency improvement AI integration and addressing industry-specific needs	2023/7	Comprehensive Review
[66]	Intelligent monitoring in machining	Online signal collection State recognition Intelligent decision-making	Meeting increased machining quality demands, issues in traditional techniques, and the need for advanced intelligent monitoring solutions Developing integrated intelligent systems for real-time monitoring	2024/0	Thematic Review
[67]	AI and ML in machining processes	Cutting forces prediction Tool wear prediction Machining parameter optimization	Integrating AI and ML into legacy systems Expand AI/ML applications for better process efficiency, energy reduction, and surface quality improvement	2024/0	Overview Review
[68]	Energy efficiency in machining	Energy consumption modelling Optimization techniques	Optimizing energy consumption AI to achieve energy savings of up to 20%	2024/3	Focused Review
[69]	Optimization algorithms in machining	Parameter optimization, process efficiency, surface quality improvement	Challenges in adapting algorithms to diverse machining processes Refining algorithms for enhanced efficiency, sustainability, and customization manufacturing	• 2024/2	• Thematic Review

Table 1 (continued)

References	Focus area	Key topics	Challenges and trends	Publication year/citations	Type of review
Present work	AI, ML, and DL in Machining and Sustainable Energy Applications	Systematic Review: Consortium 182 articles into clusters based on keywords	Critical literature review of each cluster	• 2025/–	• Systematic Literature Review

This study is crucial as it establishes a benchmark for future research by providing a framework to understand how AI, ML, and DL contribute to machining and sustainable energy practices. It will empower researchers and industry professionals to enhance AI, ML, and DL-driven manufacturing strategies, such as process optimization, intelligent monitoring, energy conservation, and sustainable production methods. The overarching aim is to enable the integration of AI, ML, and DL in smart manufacturing, ultimately fostering a more efficient, intelligent, and sustainable industrial ecosystem.

The incorporation of AI and ML into machining processes not only enhances operational efficiency but also revolutionizes conventional manufacturing models. By integrating AI, ML, and DL technologies, machining operations achieve greater precision, adaptability, and cost-effectiveness. These advancements substantially reduce energy consumption and waste production, thereby supporting sustainable manufacturing objectives. AI and ML enable real-time monitoring and predictive maintenance, prolonging machinery lifespan and minimizing downtime by identifying and addressing potential failures in advance.

Unlike previous reviews that primarily focus on the broad applications of AI, ML, and DL in manufacturing, this study examines the specific challenges of integration and optimization strategies in machining processes, providing in-depth insights into system adaptability and operational efficiency. The review distinctly addresses the real-world applicability of these technologies, providing evidence-based recommendations that bridge the gap between theoretical research and practical implementation in industrial settings.

This paper is systematically organized to provide a comprehensive review. Section 1 Introduction outlines the motivation, significance, and research objectives, emphasizing the need for AI, ML, and DL advancements within machining. Section 2 Materials and Methods details the data collection process, specifically in Sect. 2.1 Data Search Strategy, followed by cluster formation using VOSviewer in Sect. 2.2, and Sect. 2.3 outlines the Cluster-Wise Systematic Literature Review Procedure. Section 3 Cluster-Wise Critical Review of Literature categorizes the selected studies into eight thematic clusters. Section 4, Key Research Themes and Trends, includes Sect. 4.1, Comparative Analysis of Clusters, which highlights performance metrics, application scope, and limitations. Section 4.2 Key Observations Across Clusters, Sect. 4.3 Contribution to Energy Efficiency and Sustainability, Sect. 4.4 Challenges identifies critical challenges, such as data quality issues, computational limitations, model interpretability, and the industrial scalability of AI models, and Future Research Directions. Finally, Sect. 5 Conclusions summarizes the study's findings, highlighting the transformative role of AI, ML, and DL in machining, its contribution to smart manufacturing, and recommendations for bridging the gap between academic research and industrial implementation.

2 Materials and Methods

2.1 Data Search Strategy

Data for this systematic review were searched using the Scopus database. The primary objective was to investigate the convergence of AI, ML, and DL in machining processes, with a focus on energy efficiency and sustainability. The study employed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure a structured and transparent approach to conducting a systematic literature review of AI, ML, and DL applications in machining for sustainable energy, refer to Fig. 2. A comprehensive search query was generated with the keywords as follows:

> TITLE-ABS-KEY ("machine learning") OR ("artificial intelligence") OR ("Deep Learning") AND (machining) AND (energy) OR (sustainability).

The search yielded 331 results. To maintain consistency and accessibility, the search was limited to papers published in English, resulting in 316 documents. The dataset was further improved by selecting peer-reviewed articles, resulting in 178 publications. A manual review removed items irrelevant to the study's topic, and the final dataset consisted of 155 articles (140 research articles and 15 reviews). The cluster on digital twins (18) and real-world case studies (9) results in 182 documents for review.

After the initial retrieval of 331 articles based on search criteria, each article underwent a rigorous relevance check, retaining only those that explicitly integrated AI, ML, or

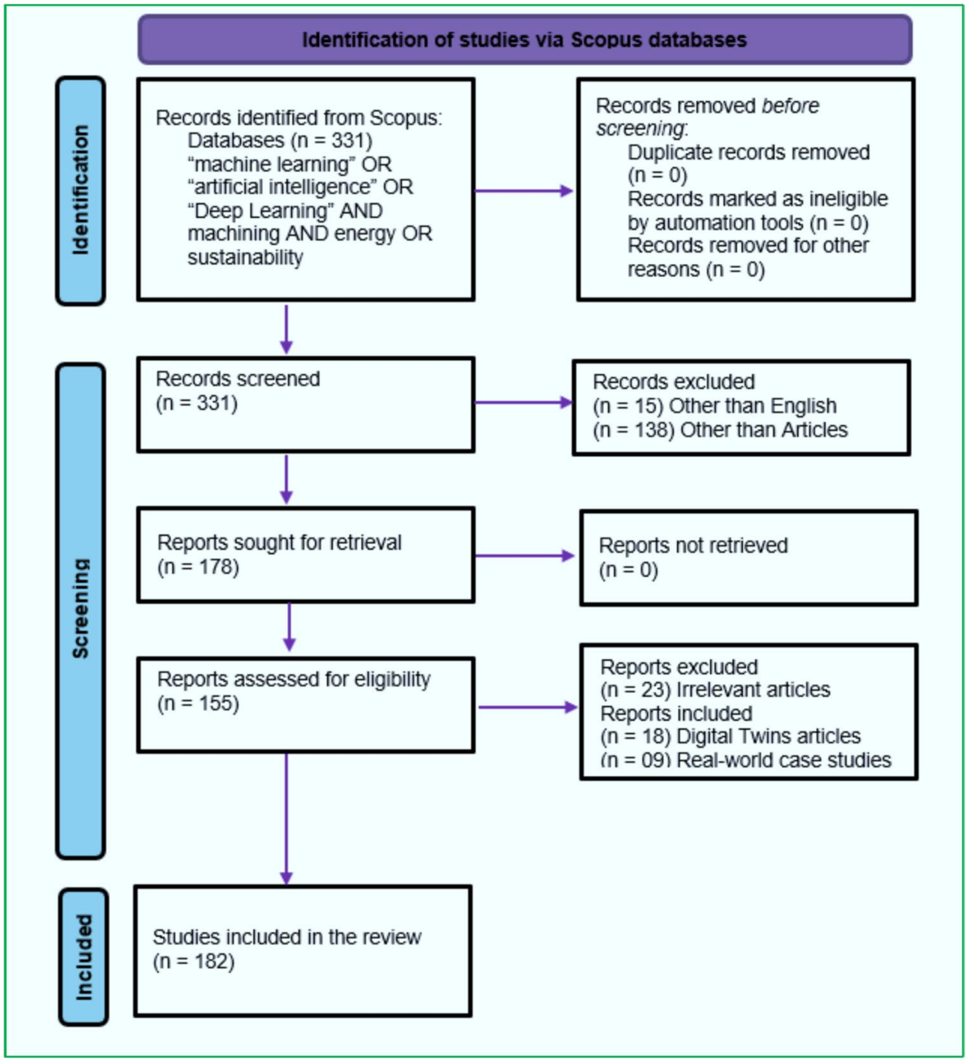


Fig. 2 Systematic review workflow illustrated by PRISMA

DL with machining processes, and focusing on recent advancements and critical reviews within the last five years. This relevance check was based on a dual screening of abstracts and conclusions, ensuring alignment with research themes. The categorization process was methodically executed using VOSviewer, which provided a network analysis of keywords and their interrelations. This confirmed thematic saturation and revealed emerging trends that were not initially apparent. The methodology identified nuanced clusters, such as"Adaptive Control Systems in Machining"and"AI-enhanced Predictive Maintenance,"highlighting specific innovations and gaps in the current research landscape. These clusters were cross-validated with recent patents and industry practices to ensure they reflected current and actionable AI applications in machining operations. The study included a validation step, where cluster outcomes were reviewed to ensure the robustness and relevance of the categorization.

2.2 Cluster Analysis Using VOSviewer

Cluster analysis using author keywords in VOSviewer reveals trends in research, knowledge structure, and collaboration patterns. It helps identify dominant themes, emerging topics, and research gaps as part of a systematic literature review, informing future research directions. Additionally, it enhances understanding of interdisciplinary connections and increases visibility. This analysis enables policymakers to develop strategic research plans and allocate resources effectively to high-impact areas. It is a powerful tool for mapping scientific landscapes and optimizing research contributions. VOSviewer (version 1.6.20) was utilized in the present systematic literature review. The author keywords were used to make clusters. The cluster analysis categorized 140 selected articles into nine thematic clusters. The clusters were assigned names relevant to a group of keywords, and each cluster, along with its associated author keywords, is shown below.

- Cluster 1: Advanced sensing and prognostics (12): acoustic emission, chatter detection, industry 4.0, computer vision, deep learning, EDM, machining, neural networks, process monitoring, prognostics and health management, signal processing, tool condition monitoring.
- Cluster 2: Machine learning and optimization in manufacturing (10): artificial intelligence, artificial neural network, clustering, genetic algorithm, machine learning, machine learning technique, prediction model, optimization, transfer learning, support vector machine.
- Cluster 3: Energy efficiency and optimization techniques (9): ANFIS, ant colony optimization, evolutionary computation, energy, energy conservation, energy-efficient machining, energy consumption, energy efficiency, energy prediction, power consumption.
- Cluster 4: Intelligent machining processes (8): CNN, convolutional neural network, deep reinforcement learning, milling, grinding, machining processes, machining process, milling process.
- Cluster 5: Smart and sustainable manufacturing (8): Manufacturing, smart manufacturing, sustainability, sustainable manufacturing, sustainable machining, surface roughness, step-nc, surface quality.
- Cluster 6: Advanced algorithms in machining (7): CNC machine tools, CNC machining, deep reinforcement learning, neural network, optimal control, prediction model, ultra-precision machining.
- Cluster 7: Lubrication and tool wear management (7): Lubrication, MQL, nanofluids, minimum quantity lubrication, tool wear, tool wear prediction, tool condition monitoring.
- Cluster 8: CNC and deep learning applications (4): CNC, deep learning, machine tools, turning.
- Cluster 9: Neural networks and energy management (4): ANN, SVM, Ti–6 Al–4 V.

2.2.1 Refining and Updating Clusters

After generating clusters using VOSviewer software, each cluster was analyzed based on its associated keywords and assigned a descriptive name relevant to its content. To enhance clarity and coherence, Clusters 3, 5, and 9 were merged into a unified ‘Sustainability Group,’ and Cluster 8 ‘Digital Twins’ was added. Consequently, the refined clustering resulted in the following eight clusters:

- Cluster 1: Advanced sensing and prognostics.
- Cluster 2: Machine learning and optimization in manufacturing.
- Cluster 3: Sustainability group.
- Energy efficiency and optimization techniques.
- Smart and sustainable manufacturing.
- Neural networks and energy management.
- Cluster 4: Intelligent machining processes.
- Cluster 5: Advanced algorithms in machining.
- Cluster 6: Lubrication and tool wear management.
- Cluster 7: CNC and deep learning applications.
- Cluster 8: Digital twins.

2.2.2 Justification for Choosing VOSviewer for Cluster Analysis

VOSviewer is chosen for cluster analysis due to its reliable and well-established capabilities in bibliometric analysis, as well as its ability to clearly and intuitively display scientific landscapes. The software utilizes sophisticated algorithms that analyze keyword co-occurrences, citation patterns, and bibliographic coupling to uncover hidden thematic connections between scholarly articles. Its interactive visualization features enable in-depth exploration of interconnected themes, allowing researchers to grasp complex relationships within the data. Additionally, VOSviewer is widely recognized and utilized in academic research during literature review processes, assuring the results'reliability, credibility, and reproducibility. VOSviewer offers clear visualizations, sophisticated clustering algorithms, engaging interactive features, and academic credibility. These qualities make it the ideal analytical tool for extracting valuable thematic insights from large bibliometric datasets.

2.2.3 Validation Process of Thematic Clusters

The thematic clusters identified using VOSviewer were carefully validated through a structured, multi-step approach:

- *Initial keyword-based analysis*: clusters were first examined based on the frequency, relevance, and co-occurrence strength of keywords. This step ensured thematic coherence and helped identify core themes clearly and distinctly.
- *Expert review and refinement*: each identified cluster underwent expert qualitative analysis to ensure a meaningful interpretation. Expert evaluation involved assessing thematic cohesiveness, relevance to the domain, and consistency in keyword associations.
- *Merging closely related clusters*: clusters exhibiting significant thematic overlap, particularly in sustainability-related areas (such as energy efficiency, smart manufacturing, sustainable machining, and energy management), were merged into a comprehensive'Sustainability Group'and eight cluster ‘digital twins’ were added. This decision enhanced clarity and minimized redundancy,

enabling a unified and coherent exploration of sustainability themes.
- *Final cross-validation*: following the merger, the refined clusters were reassessed against the original datasets to confirm their representational accuracy and thematic integrity. Cross-validation with recent literature ensured robustness and contemporary relevance of the clusters.

The rigorous validation approach ensured that each thematic cluster accurately and meaningfully represents distinct areas of research within advanced manufacturing, machining processes, and sustainability research.

2.3 Cluster-Wise Systematic Literature Review Procedure

After generating clusters and assigning names based on author keywords, a systematic search was conducted within the dataset of 140 articles. Each keyword from a cluster was used to filter relevant articles, and all identified articles were grouped into their respective clusters. The same procedure was applied to all clusters. A critical review was conducted for each cluster, extracting key insights and organizing them in a tabular format. The tables were then analyzed to identify patterns, trends, and key findings, resulting in a comprehensive conclusion for each research domain.

3 Cluster-Wise Critical Review of Literature

This section provides a structured and elaborate analysis of the chosen articles grouped into thematic clusters to capture the various applications and revolutions of AI, ML, and DL in the machining operations. Each cluster is critically evaluated to determine the existing state of studies, recognize critical breakthroughs, and note continued challenges and gaps in the literature. This systematic methodology illustrates the complex influence of these technologies on machining operations and assists in identifying areas most likely to benefit from future research. By deconstructing the literature into thematic categories, the study gives a broad overview that facilitates knowledge synthesis and drives the strategic planning of future technological advancement in intelligent manufacturing systems.

3.1 Cluster 1: Advanced Sensing and Prognostics

The “Advanced Sensing and Prognostics” cluster-1 focuses on applying advanced sensing techniques and predictive models in machining operations. The emphasis is on real-time monitoring, predictive maintenance, and optimization through acoustic emission sensing, signal processing, and ML models such as ANFIS, SVM, convolutional neural network (CNN), and RNN. These innovations aim to improve tool wear prediction, machining efficiency, and sustainability in manufacturing operations, as shown in Fig. 3.

Table 2 shows prognostics, sophisticated sensing, and optimization methods in diverse machining processes and explores how ML models can improve tool wear prediction and machining efficiency. Teimouri et al. [70] and Nain et al. [71] optimized EDM and WEDM parameters using ANFIS and SVM models. They emphasized incorporating optimization methods with ML models to enhance parameter selection and process monitoring. Proteau et al. [72] and Shah et al. [73] examined various models to predict tool wear. While Shah et al. [73] used LSTM models and acoustic emission (AE) sensors for real-time tool wear monitoring during milling, Proteau et al. [72] used RNN and linear regression to link cutting energy with tool wear. The potential of ML algorithms to improve tool wear management and predictive monitoring was highlighted in both studies. Li et al. [74] and Wang et al. [75] focused on the use of audio

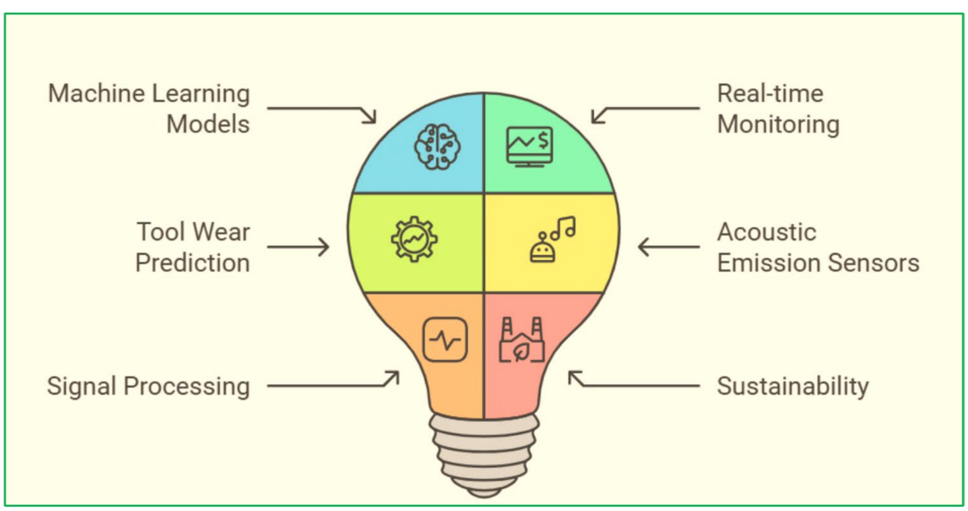


Fig. 3 Cluster 1: advanced sensing and prognostics

Table 2 Key Themes and Insights on Advanced Sensing and Prognostics: Cluster 1

References	Research focus	Methodology	Key findings	Implications for advanced sensing	Implications for prognostics	Recommendations
Teimouri et al. [70]	Optimizing EDM parameters	ANFIS models Ant colony optimization	ANFIS models optimized EDM input conditions	ANFIS models improve process monitoring	Optimization techniques enhance tool wear Process prediction	Integrating different optimization techniques with ANFIS models
Nain et al. [71]	Modelling wire EDM Super alloy Udimet-L605	SVM Taguchi Method	SVM with radial-basis kernel best model For cutting speed and WWR	SVM accurately models machining processes	Improved parameter selection for better tool life	Explore more sophisticated ML models for WEDM
Proteau et al. [72]	Predicting tool wear Specific Cutting Energy	RNN Linear regression	High correlation between specific cutting energy and tool wear	RNN models enhance predictive monitoring	Specific cutting energy can be used as a reliable tool	Development of RNN models for broader machining applications
Li et al. [74]	Real-time monitoring of tool wear Audio Signal Processing	Audio sensors PCA	High accuracy	Audio signals offer a cost-effective sensing method	Non-intrusive sensors	Industrial implementation of audio signal-based tool wear monitoring systems
Wang et al. [75]	Characterizing machining mechanisms Acoustic Emission	AE sensors RF NFRP	AE sensors can predict cutting conditions	AE sensors can detect variations in material removal	AE can predict tool wear progression	AE signals and different machining conditions for composites study required
Laddada et al. [76]	Monitoring tool wear Predicting remaining helpful life	CCWT IELM	Accurately predict tool	ML for detailed process monitoring	Effective prediction based on real-world data	Integration of wavelet transforms with other ML techniques
Liu et al. [77]	Predicting discharge status WEDM Spark Image Analysis	CNN GRU	Effectively predict discharge status	High-speed imaging	Improved discharge status monitoring	Application of CNN-GRU models to other machining processes
McDonnell et al. [46]	Parameter optimization Laser surface texturing	Neural networks	Reduce experimental time Development time	Enhance parameter optimization	Reduced cost for process optimization	Application of neural networks to various laser processing tasks
Mollik et al. [85]	Effects of vibration on micro EDM	Piezo vibrator SEM analysis	Low discharge energy	Improves debris removal and process stability	Enhanced tool wear management	Further exploration of vibration effects under different EDM conditions
Shah et al. [73]	Monitoring tool wear during milling Acoustic Emission	AE sensors Morlet wavelets SinGAN, LSTM models	LSTM model predicts tool wear with high accuracy	Real-time monitoring	Accurate tool wear prediction Minimal data	Development of online DL TCM systems using LSTM models
Schueller et al. [78]	Generalizability of TCM systems	Ensemble learning Simulated noise augmentation	Ensemble model performed best for TCM	Improve TCM accuracy Generalizability	Enhanced TCM systems	Simulated noise augmentation to improve model robustness

Table 2 (continued)

References	Research focus	Methodology	Key findings	Implications for advanced sensing	Implications for prognostics	Recommendations
Elumalai et al. [79]	Impact of SiC nanopowder on micro EDM of Inconel 718	SVR RFM	Improved MRR by 163% Reduced TWR and surface roughness by 24%, 17%	Nanopowder enhances machining performance	Improved process stability Tool life	Application of nanopowders in other EDM processes
Hazzan et al. [86]	Reshaping of worn cutting tools Laser reconditioning	Computer vision Machine vision Path planning	Successful reconditioning of worn tungsten carbide inserts	Aids in precise reconditioning	Extends tool life and Reduces need for energy-intensive recycling	Implementation of laser reconditioning in various industrial applications
Walk et al. [16]	DL for sustainable production Usage	Computer vision	Reduction in CO2 emissions by 12% for tools 44% for rotating anodes	Improves wear detection Improves process parameters	Enhanced decision-making for sustainable production	Adoption of DL in product-service systems for sustainability
Jauhari et al. [37]	Intelligent real-time chatter detection in milling	VMD-BOA WSST TL with modified DCNNs	98.21% accuracy	Advanced signal processing	Improved surface quality Improved tool life	Development of intelligent real-time chatter monitoring systems
Asadi et al. [87]	Sensitivity of AE signal attributes Milling	Wavelet transforms Statistical analysis	Significant impact of cutting speed Feed rate Coating material	Better process understanding	Enhanced process control Optimization	Integration of AE signal analysis with AI for online monitoring Predictive systems
Upadhyay et al. [88]	WEDM Wire Breakage Prediction	LR RF DT Gaussian Naive Bayes	RF achieved 100% accuracy	Enhanced prediction of wire breakage	Improved productivity Product Quality	Utilization of binomial classification algorithms
Ye et al. [80]	Real-time micro-EDM process monitoring	DL, D-CNN Transformer encoder	Achieved 96% classification accuracy Improved process stability	Real-time monitoring	Enhanced machining quality Enhanced process stability	Adoption of CNN-TSE models for adaptive regulation
Dogan et al. [89]	Reducing energy footprint in machining Ti-6 Al-4 V Energy Consumption Tool Life	DL Sensor signals WS2-oil suspension	Over 90% classification accuracy for tool change timing	Accurate tool life prediction	Full utilization of tool's useful life	Adoption of new cooling/lubrication methods and DL techniques
Abbas et al. [90]	Effect of tool material on surface integrity EDM	RSM XGBoost RF DT	XGBoost shows maximum accuracy	Enhanced surface characteristic prediction	Optimized machining parameters	Integration of RSM and ML
Xu et al. [91]	Energy consumption of tools Ultra-Precision Machining	LSTM G-code interpreter	Achieved R^2 value of 0.93	Accurate energy consumption prediction	Better energy planning Better strategy	Utilize 1DCNN-LSTM-Attention models for sustainable ultra-precision machining practices

Table 2 (continued)

References	Research focus	Methodology	Key findings	Implications for advanced sensing	Implications for prognostics	Recommendations
Mirad et al. [92]	Tool wear prediction in ultrasonic machining of Inconel 718	Acoustic emission sensor SVM	96.13% accuracy	Real-time tool wear monitoring	Improved tool life Improved machining accuracy	Implement real-time monitoring systems
Shunhu et al. [93]	Drilling quality CFRP Energy consumption	CNN-LSTM	Optimal parameters ensure low power consumption High hole quality	Accurate prediction of delamination Energy usage	Enhanced drilling quality Reduced energy consumption	Optimize drilling parameters to balance energy efficiency
Ye et al. [32]	Ensuring surface quality Micro-EDM	On-machine metrology (OMM) In-process roughness prediction (IPRP) Bayesian regression	Surface roughness variations < = 0.1 µm	Accurate surface quality	Improved surface quality consistency	Implement a closed-loop control strategy
Gonzalez-Sanchez et al. [81]	Detecting and segmenting single craters WEDM Crater Characterization	YOLOv8 object detection Vision Transformer-based instance segmentation	Significant variations in crater contour and area	Enhanced crater detection through computer vision	Better process optimization	Implement YOLOv8 and Vision Transformer techniques
Patange et al. [82]	AI-based tool condition monitoring	PCA k-means clustering	Effective tool condition classification with minimal data	Improved tool condition monitoring	Reduced need for extensive data collection	Use PCA and k-means clustering with limited data
Yue et al. [32]	DL X-ray Diffraction Analysis	CNNs	High reliability in predicting phase fractions with a mean-square error of 2.6 × 10–4	Reliable analysis of diffraction patterns	Enhanced accuracy	Apply well-tuned CNNs for high-throughput analysis
Ishfaq et al. [13]	Nano-graphene mixed rice bran oil for sustainable EDM	ANN modelling NSGA-II optimization Taguchi	98.8% improvement in MRR 93.9% reduction in SEC 99.96% less CO2 emission	Improved EDM sustainability	Significant reduction in energy consumption Fewer carbon emissions	Use nano-graphene mixed rice bran oil and ANN-NSGA-II for sustainable EDM processes
Omole et al. [94]	Tool wear prediction in end milling of single-phase tungsten	1D CNN for signal forecasting RF for signal classification	Accurate tool wear prediction with a mean absolute error of 3.37	Enhanced tool wear monitoring	Maximized tool life Less workpiece damage	Implement 1D CNN and RF models for reliable tool wear prediction in tungsten machining

signal processing and AE sensors for real-time tool wear monitoring and characterizing machining mechanisms. Li et al. [74] demonstrated the effectiveness of audio signals for non-intrusive and cost-effective sensing. At the same time, Wang et al. [75] showed that AE sensors could predict cutting conditions and material removal variations, underscoring the utility of acoustic and audio sensors in advanced sensing applications.

Laddada et al. [76] and Liu et al. [77] explored different ML models for tool wear prediction and discharge status monitoring. Laddada et al.[76] used CCWT and IELM to predict tool wear and remaining useful life, while Liu et al. [77] employed CNN and GRU for spark image analysis in WEDM. Both studies highlighted the importance of combining ML techniques for high prediction accuracy and improved process stability. Schueller et al. [78] and Elumalai et al. [79] investigated tool condition monitoring (TCM) and EDM performance. Schueller et al. [78] employed ensemble learning and simulated noise augmentation to enhance the accuracy and generalizability of the TCM system. In contrast, Elumalai et al. [79] explored the impact of SiC nanopowder on micro EDM, showing significant improvements in material removal rate (MRR) and tool wear reduction. These studies illustrated the benefits of advanced ML techniques and material enhancements in machining processes. McDonnell et al. [46], Walk et al. [16], and Ye et al. [80] focused on optimizing machining parameters and ensuring sustainable production. McDonnell et al. [46] used neural networks for laser surface texturing, reducing experimental and development time, while Walk et al. [16] applied DL for sustainable production, achieving significant CO_2 emission reductions. Ye et al. [80] utilized DL models for real-time micro-EDM process monitoring, demonstrating improved process stability and machining quality. These studies highlighted the role of ML and DL techniques in optimizing machining processes and promoting sustainability. Gonzalez-Sanchez et al. [81], Patange et al. [82], and Yue et al. [32] explored advanced sensing and monitoring techniques in EDM and other machining processes. Gonzalez-Sanchez et al. [81] used YOLOv8 and Vision Transformer-based instance segmentation for crater characterization in WEDM. Patange et al. [82] employed PCA and k-means clustering for AI-based tool condition monitoring with limited data. Yue et al. [32] applied CNNs for high-throughput X-ray diffraction analysis, achieving high reliability in predicting phase fractions. These studies emphasized advancements in sensing and monitoring technologies for improved machining accuracy, efficiency and active noise cancellation [83].

Cluster-1, "Advanced Sensing and Prognostics," highlighted the research on advanced sensing, prognostics, and optimization in machining processes using various ML models like ANFIS, SVM, RNN, CNN, GRU, LSTM, and ensemble learning. These models improve process monitoring, parameter optimization, and tool wear prediction in EDM, WEDM, milling, and laser processing. Key findings include enhanced predictive accuracy, improved process stability, and reduced energy consumption and CO_2 emissions. Integrating audio and acoustic emission sensors, advanced signal processing, and optimization techniques demonstrates the potential for cost-effective real-time monitoring. Innovative materials such as SiC nanopowder and nano-graphene dielectric enhance machining performance and sustainability.

Cluster-1, "Advanced Sensing and Prognostics," suggests that future research in advanced machining and tool condition monitoring should prioritize the integration of various ML models, such as CNNs, RNNs, LSTMs, and ensemble techniques, alongside different sensing technologies like acoustic emission sensors, audio signal processing, and computer vision [84]. Emphasizing sustainable practices, such as utilizing nano-graphene dielectrics and efficient energy consumption prediction models, is essential. Future research should also focus on developing adaptive and robust online monitoring systems to ensure superior machining quality and efficiency across various industrial applications.

3.2 Cluster 2: Machine Learning and Optimization in Manufacturing

Cluster-2 "Machine Learning and Optimization in Manufacturing" investigates the applications of AI, ML, and DL techniques and optimization algorithms in manufacturing. It illustrates how ML models like RF, SVM, and ANN can improve energy efficiency, machining parameter optimization, and tool condition monitoring when combined with genetic and ant colony optimization techniques. The cluster importance is described in Fig. 4.

Table 3 provides a detailed review of studies that fall within the scope of the cluster as per keywords. These studies cover energy efficiency, machining parameter optimization, surface roughness prediction, tool condition monitoring, and sustainable manufacturing. Energy efficiency and optimization are central themes, with numerous studies dedicated to reducing energy consumption and improving process planning and scheduling.

Zhang et al. [95], Wang et al. [96], and Tang et al. [97] employed genetic algorithms, deep reinforcement learning, and ant colony optimization to achieve significant energy savings. In particular, Zhang et al. [95] reported a 10.7% reduction in energy consumption using a mutation-combined ACO algorithm. Machining and surface roughness optimization are also critical areas of research. Studies by Dubey et al. [98] and Abbas et al. [90] highlighted ML models such as Random Forest (RF) and XGBoost to predict and optimize surface roughness. These models provide high prediction accuracy, help achieve desired surface quality, and

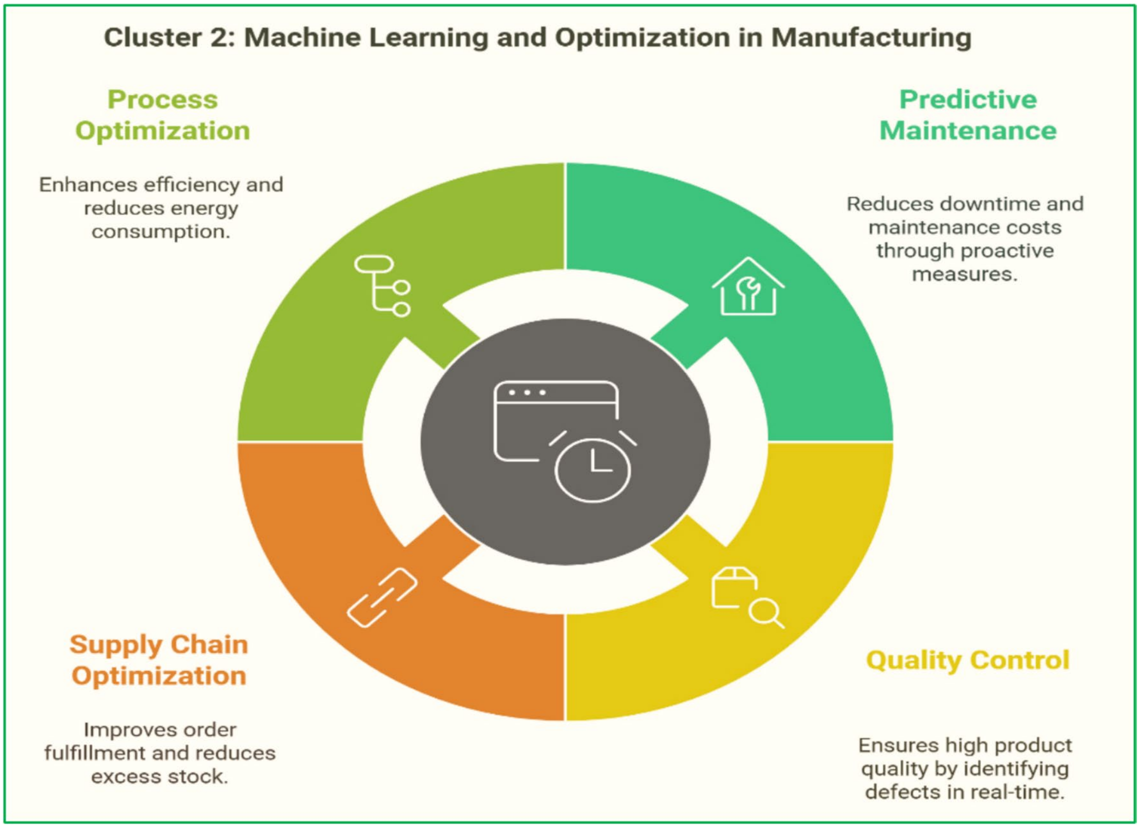


Fig. 4 Cluster 2: machine learning and optimization in manufacturing

minimize tool wear. Real-time monitoring and prediction of tool conditions are essential for efficient manufacturing processes. Jauhari et al. [37] and She et al. [99] utilized transfer learning and BiLSTM models to enhance the accuracy and reliability of tool wear predictions.

The real-time monitoring systems achieved a high classification accuracy of 98.21% in detecting tool chatter [37]. Sustainable manufacturing practices were emphasized in studies by Ishfaq et al. [13] and Celent et al. [100], which explored using renewable dielectrics and environmentally friendly materials to reduce carbon emissions and improve energy efficiency. Ishfaq et al. [13] reported significant improvements in machining sustainability using nano-graphene mixed rice bran oil. These studies'methods include various ML models, such as ANN, SVM, and DL techniques, which were applied to predict and optimize machining parameters and energy consumption.

Maurya et al. [10] demonstrated ANN and GA for precise thermal error prediction in high-speed spindles. Optimization algorithms GA, ACO, and non-dominated sorting genetic algorithm (NSGA-II) [101] were frequently employed to solve complex optimization problems, as seen in studies by Salem et al. [102] and Khalilpourazari et al. [18]. Experimental and simulation methods, such as Power Spectral Density and Monte-Carlo Ray Tracing (MCRT), provide data for developing and validating models and finite element simulation [103]. Meng et al. [104] and Kalandyk et al. [51] effectively combine experimental data with ML for process optimization. A domain knowledge-integrated optimization design framework is also useful [105].

Cluster 2 "Machine Learning and Optimization in Manufacturing" findings indicate that integrating ML and optimization techniques significantly enhances energy efficiency, machining performance, and real-time monitoring. Dubey et al. [98] achieved high prediction accuracy for surface roughness using RF models. Real-time monitoring systems developed by Jauhari et al. [37] show high classification accuracy for detecting tool chatter. Sustainable practices using renewable dielectrics and environmentally friendly materials demonstrate the potential for reducing the environmental impact of machining processes [13]. The implications for ML and optimization are substantial. ML models provide robust predictions and optimize complex systems, enhancing efficiency and sustainability. Optimization techniques, such as GA and ACO, improve process parameters and energy consumption [106], resulting in more efficient and eco-friendly manufacturing processes, fuzzy logic also

Table 3 Advancements in Machine Learning and Optimization for Manufacturing: Cluster 2

References	Research focus	Methodology	Key findings	Implications for machine learning	Implications for optimization	Recommendations
Tang et al. [97]	Real-time measure of grinding processes Mill load measure	Experimental analysis Power spectral density GA-PLS models	Rheological properties of pulp affect amplitude Frequency	Soft-sensor models	Improved grinding performance	Further research on industry-scale ball mills
Teimouri et al. [70]	Correlating EDM parameters MRR Surface roughness Rotary tool with magnetic field in EDM	Experimental observations ANFIS models, CACO technique	CACO technique optimizes EDM process parameters for maximum MRR and specified SR	ANFIS models effectively predict EDM outcomes	Enhanced EDM process parameters through CACO optimization	Apply the CACO technique in various energy regimes to refine process parameters
Tong et al. [112]	Reducing energy consumption	Improved genetic algorithm Dynamic clustering	Less heating time Increased furnace utilization	GA improved scheduling	Enhanced scheduling	Adoption of dynamic clustering and stacking optimization
Zhang et al. [95]	Integration of process planning and scheduling Energy-saving	Energy evaluation model Mutation-combined ACO algorithm	Reduces energy consumption by 10.7% compared to traditional methods	Selection of energy-efficient process plans	ACO algorithm improves manufacturing Energy efficiency	Implementation of mutation-combined ACO for integrated process planning and scheduling in flexible manufacturing systems
Jovic et al. [113]	Estimation of wood bonding strength sensitivity Power utilized	AI	Type of adhesive Sensitive factor	AI tools are adequate for nonlinear process analysis	Optimized wood machining parameters	Utilization of AI tools in the wood industry to reduce experimental costs
Wang et al. [96]	Energy-efficient machining STEP-NC Sustainable production	Optimization model Improved ACO solution	Efficiency enhanced by 25%	Facilitates comprehensive machining scheme generation	Improved energy optimization	Implementation of STEP-NC-based optimization models for energy-efficient machining schemes
Miriyala et al. [114]	Nonlinear system identification Integrated grinding circuits Energy efficiency	DRNNs LSTM Multi-objective framework	Optimal LSTMs achieved 99% accuracy	DRNNs with LSTMs offer accurate data-based models for complex systems	Improved control Improved optimization in grinding circuits	Implement DRNNs for online control and optimization
Meng et al. [104]	Solar power satellite (SPS) optimization Improving optical efficiency Improving irradiance uniformity	ACO algorithm Dynamic source-target mapping Monte-Carlo ray tracing (MCRT)	ACO combined with MCRT finds suitable aiming vectors Enhancing optical efficiency and irradiance uniformity	ML enhances solar reflector optimization	ACO improves optical efficiency	Apply ACO and MCRT for optimal design and operation of solar power satellite systems

Table 3 (continued)

References	Research focus	Methodology	Key findings	Implications for machine learning	Implications for optimization	Recommendations
Khalilpourazari et al. [18]	Optimizing turning process parameter in uncertain environments Energy efficiency	Robust mathematical model AI-based solution techniques Worst-case sensitivity analysis	Significantly reduces energy consumption Shows robustness in uncertain conditions	Effectively solve complex, nonlinear optimization problems	Robust optimization model ensures energy savings Precision savings	Employ robust optimization models and AI techniques for energy-efficient machining in uncertain environments
Sharma et al. [115]	Integrated grinding circuit optimization	Chance constrained programming (CCP) DISC Fuzzy C-means algorithm Sobol sampling	DISC improves optimization by 42% over conventional techniques	ML aids in accurate sampling	DISC enhances CCP efficiency and accuracy	Use DISC for optimization in processes with sparse and uncertain data
Pawanr et al. [116]	Predicting energy consumption Machine Tools	Multi-Gene Genetic Programming Taguchi full factorial design Power analysis	Achieved high goodness of fit In training (99.77%) In testing (98.60%)	Accurately predict energy consumption	GA provided reliable energy consumption predictions	Apply AI-based genetic programming models for accurate and efficient energy consumption
Li et al. [42]	Optimizing milling process parameters Enhance energy and cost efficiency	Deep reinforcement learning BPNN Markov decision process (MDP), BP-TD3 method	Saves 95% optimization calculation time Ensures near-minimum processing cost	Deep reinforcement learning (DRL) provides efficient and accurate optimization	DRL significantly reduces computation time Ensuring cost-efficiency	Implement DRL-based optimization for milling processes
Celent et al. [100]	Multi-criteria decision-making	PROMETHEE method Multi-criteria decision support system Criteria weights sensitivity analysis	Green machining	Help to balance economic, ecological, and social aims	PROMETHEE method optimizes sustainable machining processes	Use multi-criteria decision-making approaches like PROMETHEE
Dubey et al. [98]	Minimizing surface roughness in turning operations Using nanofluids	RSM LR RF SVM	RF model outperforms others R-squared values of 0.8176 and 0.7231	ML accurately predict surface roughness with different particle sizes	RF model effectively predicts and optimizes surface roughness	Employ RF models to predict and minimize surface roughness
Lee et al. [117]	Maximizing elastic wave focusing Harvesting	DNN Genetic optimization Active learning	Optimized GRIN PnC design exhibits 3.06 times higher wave energy intensity	Effectively predict complex relationships	Enhances wave focusing Energy harvesting	Use ML to explore unconventional unit cell designs
Salem et al. [102]	Optimizing cutting conditions for sustainability	Genetic Programming Non-dominated Sorting Genetic Algorithm (NSGA-II) Clustering Multi-objective optimization	Optimal cutting conditions grouped into clusters	Improve sustainability	NSGA-II efficiently handles multi-objective optimization	Implement knowledge discovery approaches

Table 3 (continued)

References	Research focus	Methodology	Key findings	Implications for machine learning	Implications for optimization	Recommendations
Checa et al. [118]	Optimizing milling performance Optimize tool design	RF Multilayer perceptrons Bagging Virtual Reality	Best model with cutting-force inputs outperforms others	ML accurately models cutting tool performance	VR enhances training Machining optimization	Combine experimental data, ML and VR for optimization
Awan et al. [119]	Predicting energy consumption	Gaussian process regression Regression trees ANN	Correlation coefficient of 0.98 is achieved	Supervised learning techniques predict energy consumption accurately	Accurate prediction models support energy reduction in cut-off grinding	Use Gaussian process regression
Jauhari et al. [37]	Intelligent real-time monitoring	VMD-BOA WSST Transfer learning with modified pre-trained DCNNs	98.21% classification accuracy Good recognition time	Transfer learning enhances chatter detection	VMD-BOA optimizes intrinsic mode decomposition	Employ intelligent real-time chatter detection using VMD-BOA and transfer learning
Yang et al. [39]	Optimizing milling process for energy consumption Processing time Surface roughness	IoT-based data acquisition ML based performance prediction	Integrated framework improves energy consumption	IoT enhances real-time data acquisition	Improves overall milling performance	Adopt IoT and machine learning frameworks
Ming et al. [120]	Optimizing EDM parameters	RSM ELM-improved integrated beta-distribution cuckoo search (IBCS) algorithm	Improving EDM performance Sustainability	Optimize EDM processing effectively	RSM and ELM improve EDM reduce energy consumption and emissions	Use ELM and IBCS algorithm to optimize EDM processes
Zhang et al. [55]	Large manufacturing systems	DIWPSO-LSTM algorithm Improved PSO	Improves performance by over 30% in MAE and ME	Improved PSO optimizes LSTM for accurate energy consumption prediction	Enhanced prediction supports energy efficiency	Implement DIWPSO-LSTM for accurate energy consumption prediction
Samsonov et al. [57]	Optimizing workpiece positioning Orientation in CNC milling	DL Reinforcement learning (RL) Hill-climbing heuristics	RL agent solutions accelerate setup optimization	Speed up CNC setup optimization	Improves milling quality Reduces wear	Implement DL and RL for WP setup
Saldana et al. [121]	Improving SAG mill productivity Energy consumption prediction	Statistical analysis Regression ANN	Enhance production by 4.42% Reduce energy consumption by 7.62%	Optimize complex mining processes	Adjusting mill rotational speed optimizes energy consumption	Use ML models to enhance resource efficiency and production in mining
Peng et al. [122]	Multi-objective optimization on embedded processors	Micro MOEA with piecewise strategy MOEA/D framework Dynamic weight vector update mechanism	μMOEA performs well on ZDT DTLZ SMOP MaF problems	MOEA/D framework adapted for limited computing resources	Piecewise strategy optimizes subclusters effectively	Apply μMOEA for efficient optimization in embedded systems

Table 3 (continued)

References	Research focus	Methodology	Key findings	Implications for machine learning	Implications for optimization	Recommendations
Abbas et al. [90]	Impact of milling variables on surface quality Temperature Energy consumption MRR	SVM KNN ANN RF XGBoost, Genetic algorithm (GA)	XGBoost with GA optimization achieves 98% prediction accuracy Improving machining parameters prediction	Predict machining outcomes effectively	GA enhances ML model accuracy	Implement XGBoost with GA for accurate prediction and optimization
Bousnina et al. [123]	Optimizing machining parameters	RSM ANN GA	AI reduces TSEC by 44.13% Increases EE by 14.63%	Optimize energy consumption in machining	GA effectively reduces TSEC Increases EE	Use AI and GA for multi-objective optimization of machining parameters
Nguyen et al. [124]	Predicting and optimizing surface roughness Tool wear	SVR, XGB ANN NSGA-II	ANN offers the best predictive performance	ANN provides robust predictions	NSGA-II finds optimal solutions	Combine ML models and NSGA-II for optimizing machining parameters
Brahmam et al. [52]	Optimizing VM migrations for load balancing Energy efficiency Security	Bioinspired algorithms Deep reinforcement learning K Means clustering Fuzzy logic BiLSTM with RNN	4.5% reduction in makespan 4.9% increase in deadline hit ratio, 3.9% improvement in task diversity	Enhanced security Better service quality	Bioinspired algorithms improve load balancing Better energy efficiency	Integrate bioinspired algorithms and DL for efficient and secure VM migrations
Maurya et al. [10]	Thermal deformation prediction of high-speed spindles	ANN GA-based optimization	R2 values between 0.94–0.98 Accuracy of 96.26–98.82% for single-spindle 7.31% improvement for dual-spindle system	ANN models provide accurate predictions GA optimizes input parameters	Reduced thermal deformation Less power consumption	Apply ANN and GA for precise thermal error
Kalandyk et al. [51]	Optimizing spindle motion	DL Reinforcement learning	Improved machining process speed and accuracy	DL effectively maps and optimizes CNC spindle motion	RL speeds up machining Improves accuracy	Implement DL and reinforcement learning to optimize CNC machining
Gao et al. [125]	Enhancing power output of piezoelectric energy harvesters	Hierarchical auxetic structures COMSOL Multiphysics simulation ML model	Higher power output Improved energy harvesting efficiency Reduced Poisson's ratio	ML and optimization improve energy harvesting	Hierarchical auxetic structures enhance energy harvester performance	Use ML and multiobjective optimization for developing efficient piezoelectric energy harvesters
Bott et al. [126]	Framework for optimizing milling processes	ML system for data analysis Software demonstrator	Improves machining parameter optimization	ML enhances industrial process optimization	Data-driven techniques refine machining parameters effectively	Adopt ML frameworks for optimizing industrial milling processes

Table 3 (continued)

References	Research focus	Methodology	Key findings	Implications for machine learning	Implications for optimization	Recommendations
She et al. [99]	Online intelligent prediction based on indeterminate factors	BiLSTM model AE signals GA-optimized BiLSTM LSTM BP neural networks	BiLSTM model achieves 92.08% prediction accuracy Promotes sustainable manufacturing	BiLSTM models effectively predict tool wear using heterogeneous data	GA and BiLSTM improve prediction accuracy and stability	Implement BiLSTM and GA for accurate online tool wear prediction in micro-grinding
Yurtkuran et al. [127]	Estimating and optimizing power consumption	ML applied to measure power consumption	Power consumption increased by 3.14% with feed speed Reduction in power consumption compared to dry cutting	ML models accurately predict power consumption-parameter relationships	ML enhances prediction of machining processes	Utilize ML to optimize power consumption in machining processes
Patange et al. [82]	Unsupervised learning Tool fault classification in milling centers	PCA for dimensionality reduction k-means clustering for classification	Successful multi-class classification of tool faults	Unsupervised learning enables efficient tool condition monitoring	Improve tool condition monitoring with minimal data input	Implement unsupervised learning techniques for effective tool conditions
Sinha et al. [128]	Optimizing MQL grinding parameters for Inconel 625 Predictive modelling	Box-Behnken design RF Gaussian process regression	Identified optimal parameters for low tangential force High surface roughness Low specific energy GPR outperformed other models	ML models improve prediction accuracy	Optimization enhances grinding process performance	Apply optimized parameters from ML models to achieve superior MQL grinding results
Ishfaq et al. [13]	Using nano-graphene mixed rice bran oil	ANN modelling NSGA-II for optimization Taguchi's experimental design for validation	Significant improvements in MRR and SEC Reduction in CO_2 emissions	ANN and NSGA-II optimize EDM process	Use of novel dielectric improves machining sustainability	Adopt nano-graphene mixed rice bran oil in EDM processes
Wu et al. [129]	Real-time condition-based maintenance	Real-time data acquisition DL for tool condition prediction NSGA-II and TOPSIS for optimization	Reduced energy consumption by 2.51% to 7.01%	DL predicts tool conditions in real time	Real-time optimization improves energy efficiency in machining	Implement real-time condition-based maintenance

contributes [107], Fuzzy Analytic Hierarchy Process to reduce carbon emission during machining [108].

Cluster 2 “Machine Learning and Optimization in Manufacturing” recommends adopting ML and optimization techniques to enhance process efficiency and reduce energy consumption. They emphasize sustainable manufacturing practices by incorporating environmentally friendly materials and optimizing processes for minimal environmental impact. Real-time monitoring systems should be developed and deployed to predict tool conditions, improving machining accuracy and efficiency. Continued research on applying advanced ML and optimization techniques in various industrial domains is essential for ongoing improvements in efficiency and sustainability.

Future research based on Cluster 2, “Machine Learning and Optimization in Manufacturing,” should focus on enhancing the integration of advanced machine learning models and optimization algorithms across various manufacturing processes. Investigating hybrid techniques that combine different optimization methods, such as GA with RL or multi-objective optimization with DL, can further enhance process efficiency and sustainability. The expansion of real-time data acquisition and processing through IoT and edge computing should be prioritized to facilitate immediate decision-making, process adjustments, CatBoost optimization [109], topology optimization [110] and to explore energy responses [111].

3.3 Cluster 3: Sustainability Group

3.3.1 Energy Efficiency and Optimization Techniques

“Energy Efficiency and Optimization Techniques” focuses on enhancing energy efficiency and process optimization in manufacturing. The research used approaches such as ANFIS, ant colony optimization, and DL to reduce energy consumption and enhance machining performance in this cluster, as depicted in Fig. 5a. It also involves research on real-time energy monitoring and AI-powered solutions to promote sustainable industrial practices.

Table 4 highlights key themes and methodologies for enhancing energy efficiency and optimizing machining processes. Numerous studies have employed advanced computational techniques like ANFIS, ACO, and DL across various

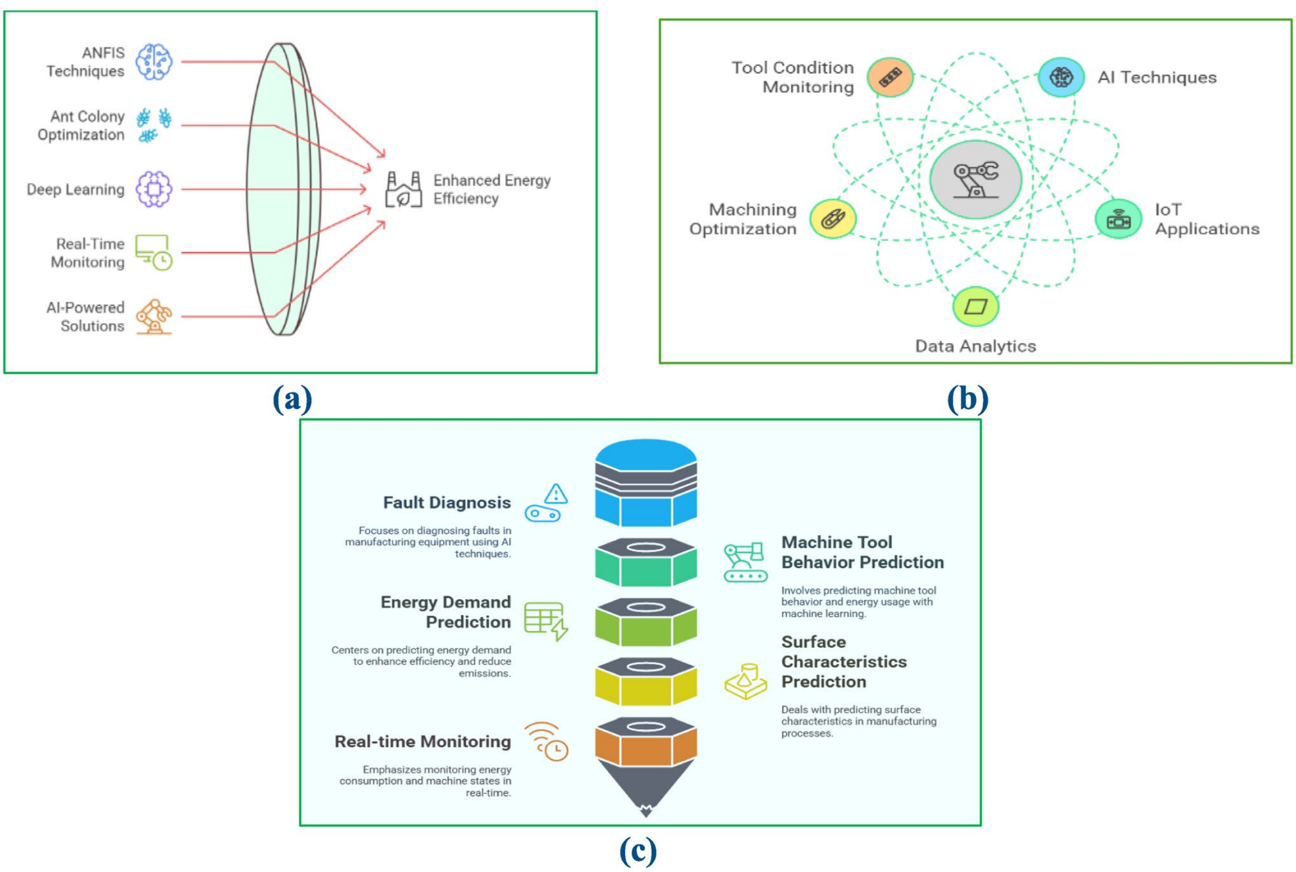


Fig. 5 Cluster 3 Sustainability Group: **a** energy efficiency and optimization techniques, **b** smart and sustainable manufacturing, **c** neural networks and energy management

Table 4 Cluster 3: sustainability group

References	Research focus	Methodology	Key findings	Implications for energy efficiency	Implications for optimization techniques	Recommendations
Energy efficiency and optimization techniques						
Teimouri et al. [70]	Optimization of EDM parameters Maximizing MRR and specified SR	ANFIS models CACO technique	CACO using ANFIS models optimized magnetic field intensity Rotational speed	Integration of magnetic field and rotary tool Improves debris flushing Improves process efficiency	Successfully optimizes EDM process parameters	Use CACO with ANFIS models as objective and constraint functions
Garg et al. [130]	Optimize milling parameters	Multi-gene genetic programming approach	Cutting speed has the highest impact on energy consumption in milling Followed by feed rate and depth of cut	Emphasizes modelling and optimizing manufacturing operations	Introduces complexity-based genetic programming	Implement complexity-based genetic programming to model energy consumption
Tong et al. [112]	Optimization of forging Heat treatment scheduling	Genetic algorithm	Reducing heating times Increasing furnace utilization	Focuses on reducing energy consumption	Proposes dynamic clustering Stacking optimization	Apply dynamic clustering and stacking optimization techniques to enhance energy efficiency
Zhang et al. [95]	Integration of process planning and scheduling	Mutation-combined ant colony optimization	Reduces energy consumption by 10.7%	Presents an energy-saving approach	Process planning and scheduling	Implement mutation-combined ant colony
Wang et al. [96]	Optimization of machining schemes	Improved ant colony optimization (ACO)	Achieved 25% efficiency improvement in machining schemes	Utilizes STEP-NC for energy-efficient machining solutions	Optimizing machining schemes	Utilize STEP-NC and enhanced ACO methods to develop energy-efficient machining strategies
Yip et al. [131]	Energy model incorporating material recovery effect	Modified energy consumption model	Accuracy in energy component prediction increased to 83.39%, Specific energy consumption increased up to 11.2 times	Highlights the importance of material recovery	Introduces a modified energy consumption model	Incorporate material recovery factors into energy consumption models
Meng et al. [104]	Optimization of PV layout for high optical efficiency Stable irradiance	ACO algorithm Monte-Carlo ray tracing (MCRT)	ACO combined with MCRT optimizes aiming vectors of modular reflectors Balancing optical efficiency	Enhances optical efficiency	Utilizes ACO and MCRT for optimization	Apply ACO with dynamic mapping and MCRT to optimize PV layout design
Zhang et al. [132]	Real-time energy-efficient control	Deep belief networks (DBNs)	Reducing carbon emissions	Enable real-time energy-efficient control of CNC	Introduces DBNs	Implement DBNs for real-time energy-efficient control of CNC machines

Table 4 (continued)

References	Research focus	Methodology	Key findings	Implications for energy efficiency	Implications for optimization techniques	Recommendations
He et al. [56]	Energy consumption prediction	Unsupervised DL for feature extraction Supervised learning for prediction model	Improves prediction accuracy	Enhance energy planning	Accurate energy prediction in machine tools	Implement DL algorithms for data-driven energy prediction
Khalilpourazari et al. [18]	Optimization of turning parameters considering uncertainty	AI-based solution techniques	Reduces energy consumption	Optimization approach for minimizing energy consumption Improving machining precision	Robust optimization of uncertain turning processes	Adopt robust formulation and AI techniques for optimizing turning processes
Brillinger et al. [133]	Prediction of energy demand	RF	Achieves accurate prediction	Enhances accuracy of energy demand prediction	Facilitating energy-efficient machining strategies	Utilize RF or similar DT variations to predict CNC machining energy demand accurately
Frigerio et al. [134]	Online time-based policy	Real-time algorithm Estimation of stochastic processes	Online policy reduces energy consumption	Facilitates real-time control of machine states Minimize energy consumption during idle periods	Optimize energy use	Implement online time-based policies for machine state control to reduce energy consumption
Tohry et al. [135]	Boosted neural network	BNN	Boosted Neural Network accurately models power draw of HPGRs	Advances energy consumption modelling	Precise energy consumption modelling	Implement boosted neural networks for accurate energy consumption modelling
Adeniji et al. [35]	Optimization of machining processes	AI Modular physics-based models	Process queuing time (93%) Scrap cost (2%), Queuing cost (93%)	Energy efficiency (84%) Profitability in machining	Integrates AI with in-situ process characterization for DPT creation	Implement DPTs based on AI for machining process optimization
Meng et al. [136]	Prediction of extraction and energy consumption	DK-ELM modelling	Accurately predicts extraction rate Predicts energy consumption Improving feasibility	Advances soft sensor design for predicting energy consumption	Decision-making in sugar production	Implement deep feature extraction DK-ELM modelling Accurate prediction of energy consumption
Lu et al. [40]	Optimization of cutting parameters	DRL Markov Decision Process (MDP)	Improved material removal rate (45.71%) Specific cutting energy (32.27%)	Enhances energy efficiency	Optimizes multi-pass milling parameters	Implement DRL and MDP-based methods for adaptive parametric optimization
Zhang et al. [55]	Energy consumption prediction method	Improved Particle Swarm Optimization (IPSO) algorithm LSTM	Significant reductions in mean absolute error (MAE) Mean error (ME)	IPSO-LSTM method improves energy consumption prediction accuracy	Optimizes LSTM hyper-parameters	Implement IPSO-LSTM for accurate real-time prediction of energy consumption

Table 4 (continued)

References	Research focus	Methodology	Key findings	Implications for energy efficiency	Implications for optimization techniques	Recommendations
Nugrahanto et al. [137]	To improve energy efficiency	DT RF	Lower RMSE compared to traditional regression methods Enhances sustainability	Enhances energy efficiency	Sustainable manufacturing practices	Implement ML algorithms to optimize energy efficiency
Smart and sustainable manufacturing						
Chang et al. [139]	Efficient machining operation	Neural networks	Reduced non-cutting time Optimize part and table orientations	Improved flexibility Improved reliability	Reduced setup time Reduced operational costs Minimize non-cutting times	Implement neural network-based optimization techniques
Grzenda et al. [140]	Effect of initial data transformation	Genetic algorithm Neural networks	Significant improvements in prediction models	Enhanced accuracy of surface roughness predictions	Improved quality of machined surfaces Reduced waste Better resource utilization	Employ hybrid algorithms for data transformation
Liu et al. [141]	Prediction of specific cutting Specific cutting energy	ML	Hybrid approach improves accuracy	Enhanced predictive power	More efficient use of energy in machining Contribute to sustainability	Integrate ML with process mechanics for more accurate energy predictions
Tran et al. [38]	Real-time chatter detection Milling	CNN Continuous wavelet transforms	99.67% accuracy in detecting chatter	Enhanced real-time monitoring Better tool performance	Reduced material wastage Improved tool longevity	Utilize CWT and CNN for accurate and real-time chatter detection
Pandey et al. [142]	Optimizing MRR Optimized Surface roughness Vibration-assisted machining	AI-based single objective optimization	Significant improvements in MRR (230%) SR (50%)	Enhanced material removal rates Better surface quality	Improved resource utilization Improved machining efficiency	Apply AI-based optimization techniques for enhanced performance
Kim et al. [143]	Tool wear prediction under multiple machining conditions	Multi-domain mixture density network (MDN) Bayesian learning Adversarial learning	Achieved best MAE of 2.1748, RMSE of 5.6422 MAPE of 0.0350	Enhances accuracy Reducing the need for multiple models Minimizing operation cost Less Modelling costs	Contributes to sustainable production	Implement MDN with Bayesian and adversarial learning for robust multi-condition tool wear prediction
Li et al. [144]	Predicting tool wear Signal feature extraction	RF Feature normalization	Improved model adaptability Prediction accuracy improved from 68.0% to 84.1%	Enhances the adaptability and accuracy of tool wear prediction models Optimizing maintenance scheduling Tool usage	Improves tool wear monitoring Reduces waste	Use RF with feature normalization to enhance tool wear prediction accuracy and adaptability

Table 4 (continued)

References	Research focus	Methodology	Key findings	Implications for energy efficiency	Implications for optimization techniques	Recommendations
Bhattacharya et al. [145]	Predicting responses in CNC face milling	RF Statistical metrics	Effectively predicts material removal rate Surface roughness Active energy consumption	Enhanced prediction accuracy Minimum feature selection	Cost optimization Effective resource utilization Accurate process modeling	Deploy RF regressor for accurate predictions in machining processes
De et al. [146]	Predicting remaining useful life (RUL) of cutting tools	Bidirectional RNN LSTM	BiLSTM and BiGRU achieved the lowest RMSE	Enhanced predictive maintenance	Improved production quality Reduced energy consumption Timely maintenance	Implement BiLSTM and BiGRU models for accurate RUL prediction of cutting tools
Wu et al. [147]	Optimizing machining conditions for difficult-to-cut materials	Intelligent servo control system Mathematical models EDAAM	Intelligent servo control system increased material removal rate by up to ten times	Improved machining efficiency Improved accuracy	Reduced tool wear Less scrapping Extended tool life Optimized machining conditions	Use intelligent servo control for efficient machining of difficult-to-cut materials
Olalere et al. [148]	Classifying tool and workpiece conditions Tool condition monitoring Signal processing	Empirical Mode Decomposition Hilbert–Huang transform GA and ML	The KNN model performed 10 times better than the SVM	Improved tool condition monitoring	Reduced misclassification errors Optimized tool Workpiece condition monitoring	Use KNN models with feature selection for accurate tool condition classification
Neural networks and energy management in machining						
Pandya et al. [149]	Comparison of AI techniques for diagnosing faults Rolling element bearings	Wavelet packet decomposition Comparison of ANN, SVM, and MLR	LR is more effective than ANN and SVM for fault diagnosis	Highlights the potential limitations of ANN		Use logistic regression for effective fault diagnosis
Komoto et al. [150]	To predict machine tool behavior To predict energy usage based on operational data	Supervised ML algorithm	Model accurately predicted energy usage Model adapted to multiple stakeholder views	Utility of supervised learning in evolving operational models	Effective prediction of energy usage	Implement supervised learning models for adaptive and accurate energy usage predictions
Brillinger et al. [133]	Investigating ML algorithms for predicting energy demand CO2 emissions reduction Energy-efficient CNC machine tools	DT RF Boosted RF	RF achieved highest accuracy	Not directly addressed	Contributes to energy efficiency in CNC machining processes	Utilize RF for accurate energy demand prediction
Prakash et al. [151]	Predicting surface characteristics of glass fiber CO2 laser milling	ANN model	ANN model outperformed the semiempirical model in predicting milling depth with superior accuracy	Shows effectiveness of ANN	Not directly addressed	Use ANN for precise prediction of surface characteristics

Table 4 (continued)

References	Research focus	Methodology	Key findings	Implications for energy efficiency	Implications for optimization techniques	Recommendations
Xu et al. [91]	Predicting energy consumption Ultra-precision machining	1DCNN-LSTM G-code interpreter	Achieved high accuracy ($R^2 = 0.93$) in predicting energy consumption	Validates the effectiveness of advanced ML in energy prediction	Promotes energy-efficient practices	Use 1DCNN-LSTM-Attention model for accurate energy prediction
	Using power consumption data for intelligent monitoring and State prediction of CNC machine tools	Densely connected CNN with multiple outputs	High accuracy (94%) in identifying machine state and predicting feed rate	Facilitates cost-effective machine tool monitoring	Enables efficient anomaly detection Efficient energy management	Implement CNN for real-time monitoring and predictive maintenance

machining processes, significantly enhancing energy efficiency and process optimization. Teimouri et al. [70] utilized CACO and ANFIS models to optimize the EDM process, enhancing debris flushing and process efficiency. Similarly, Garg et al. [130] emphasized the importance of cutting speed, feed rate, and depth of cut in energy consumption within milling and employed a multi-gene GA approach to optimize parameters. Tong et al. [112] focused on specific manufacturing techniques and used GA to reduce energy consumption in forging and heat treatment scheduling by optimizing heating times and furnace utilization. Zhang et al. [95] and Wang et al. [96] explored ACO in flexible manufacturing systems and STEP-NC machining, respectively, reporting substantial reductions in energy consumption and efficiency improvements. Yip et al. [131] developed a modified energy consumption model for ultra-precision machining, significantly increasing prediction accuracy and specific energy consumption. Meng et al. [104] combined ACO with Monte-Carlo ray tracing to optimize PV layouts, enhancing optical efficiency. Zhang et al. [132] and He et al. [56] implemented DL techniques for real-time energy-efficient control of CNC machines and data-driven energy prediction, improving prediction accuracy and energy planning.

Recent studies have continued this trend, with Khalilpourazari et al. [18] used AI-based solutions to optimize turning processes robustly, reducing energy consumption and improving machining precision. Brillinger et al. [133] utilized random forests to accurately predict CNC machining energy demand, facilitating energy-efficient machining strategies. Frigerio et al. [134] and Tohry et al. [135] developed real-time algorithms and boosted neural networks for energy-efficient machine state control and energy consumption modeling.

Advanced techniques such as digital process twins and soft sensors have been applied to machining and sugarcane milling processes [35]. Meng et al. [136], integrated AI with in-situ process characterization for improved energy efficiency and accurate energy consumption prediction. Recent works by Lu et al. [40] and Zhang et al. [55] utilized deep reinforcement learning (DRL), Markov Decision Processes (MDP), and improved Particle Swarm Optimization (IPSO) combined with LSTM for adaptive parametric optimization and accurate energy consumption prediction. Nugrahanto et al. [137] demonstrated the application of digital twins and random forests in CNC five-axis milling, achieving lower RMSE and enhancing sustainability through improved energy efficiency. The PSO optimization technique plays a vital role [138].

The cluster improves manufacturing processes to reduce energy consumption and enhance process stability, showcasing notable trends. Figure 6 depicts energy efficiency improvements achieved by various optimization techniques. Applying DRL, Monte Carlo ray tracing (MCRT), and ACO

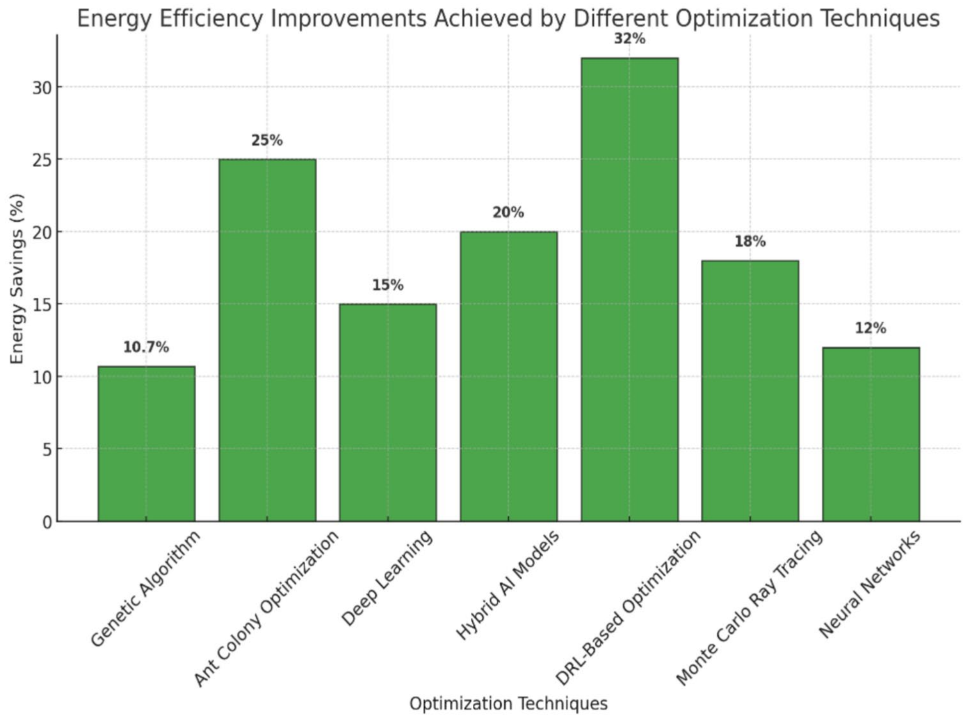


Fig. 6 Energy efficiency improvements

for energy-efficient machining. Utilize soft sensors, IoT-based real-time energy monitoring, and AI-based optimization models. Material recovery and eco-friendly machining techniques. Predictive analytics for energy-efficient CNC systems.

3.3.2 Smart and Sustainable Manufacturing

"Smart and Sustainable Manufacturing" focuses on the role of smart manufacturing techniques that use AI, IoT, and advanced data analytics to improve production and is described in Fig. 5b. It focuses on strategies for reducing resource consumption, environmental impact, and operational efficiency through intelligent decision-making and real-time monitoring.

Table 4 presents studies focusing on "smart and sustainable manufacturing" by integrating advanced computing and manufacturing techniques. The studies primarily examine the optimization of machining operations, the prediction of surface roughness, tool wear, and tool condition monitoring, utilizing methodologies such as neural networks, GA, ML, CNN, continuous wavelet transforms (CWT), and other AI-based optimization techniques.

Chang et al. [139] highlighted the benefits of neural network-based optimization in reducing non-cutting times and operational costs, thus enhancing machining efficiency and reliability. Similarly, Grzenda et al. [140] demonstrated significant improvements in surface roughness prediction through genetic algorithms and neural networks, leading to better resource utilization and reduced waste. Liu et al. [141] emphasize the role of machine learning in accurately predicting specific cutting energy, contributing to more efficient energy use in machining processes. Tran et al. [38] presented a real-time chatter detection method using CNN and CWT, achieving high accuracy and improving tool performance while minimizing material wastage. Pandey et al. [142] focus on optimizing material removal rates and surface roughness through AI-based single-objective optimization, enhancing machining efficiency and better resource utilization. Kim et al. [143] and Li et al. [144] investigate tool wear prediction using multi-domain mixture density networks (MDN) with Bayesian and adversarial learning and RF with feature normalization, respectively. Their findings indicate enhanced prediction accuracy and adaptability, reducing the need for multiple models and minimizing operational costs. Bhattacharya et al. [145] effectively predict material removal rate, surface roughness, and active energy consumption using RF and statistical metrics, optimizing costs and resource utilization. De et al. [146] and Wu et al. [147] explored tool wear prediction and machining efficiency optimization. De et al. [146] utilized bidirectional RNN, LSTM, BiLSTM, and BiGRU models to achieve low RMSE in predicting cutting tools'remaining useful life (RUL), facilitating timely maintenance and improved production quality. Wu et al. [147] implemented an intelligent servo control system and mathematical models, significantly increasing the material removal rate for difficult-to-cut materials, enhancing machining efficiency, and extending tool life. Olalere et al. [148] employed empirical mode decomposition, Hilbert–Huang transform, genetic algorithms, and ML to classify tool and workpiece conditions accurately. Their results indicate that the KNN model outperforms SVM, improving tool condition monitoring and reducing misclassification errors.

3.3.3 Neural Networks and Energy Management

"Neural Networks and Energy Management" emphasizes the expanding use of neural networks to improve energy management in manufacturing; information is depicted in Fig. 5c. The capacity of neural networks to estimate energy usage, optimize machine performance, and enhance predictive maintenance makes them vital tools for industries.

Table 4 presents key findings from research on "neural networks and energy management." Pandya et al. [149] focused on fault diagnosis in rolling element bearings. They compared various AI techniques, including ANN, SVM, and MLR, using wavelet packet decomposition. Their findings indicated that logistic regression was more effective than ANN and SVM for diagnosing faults, highlighting the limitations of ANN in this specific application. They recommended using logistic regression for effective fault diagnosis. Komoto et al. [150] predicted machine tool behavior and energy usage based on operational data. They utilized a supervised ML algorithm, which accurately predicted energy usage and adapted to multiple stakeholder views. Brillinger et al. [133] investigated various ML algorithms to predict energy demand and reduce CO_2 emissions in CNC machine tools. They compared DT, RF, and boosted RFs. The RF algorithm achieved the highest accuracy, contributing to energy efficiency in CNC machining processes. The study recommended using RF for the accurate prediction of energy demand. Prakash et al. [151] focused on predicting the surface characteristics of glass fiber in CO_2 laser milling. They employed an ANN model, outperforming a semi-empirical model in predicting milling depth with superior accuracy. Xu et al. [91] conducted two studies; the first aimed to predict energy consumption in ultra-precision machining using a 1DCNN-LSTM model with a G-code interpreter. The combination of dual-tree complex wavelet transform and variational mode decomposition enhances operational efficiency, reliability, and maintenance practices in industrial systems [152].

"Neural Networks and Energy Management" focuses primarily on AI-based energy-efficient machining techniques and notable trends.

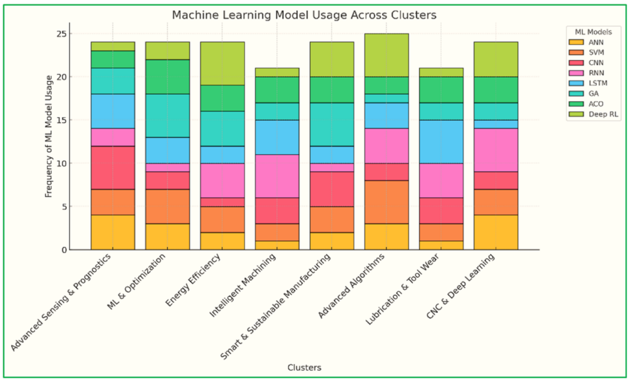
- ANN, SVM, and Ti-6 Al-4 V models for energy consumption prediction.
- Data-driven energy optimization strategies.
- Sustainable manufacturing through AI-driven energy planning.

The cluster analysis conducted with VOSviewer has delivered a thorough literature review of essential trends in the optimization of machining and manufacturing. AI, ML, DL, and cutting-edge sensing technologies substantially enhance these clusters'energy efficiency, sustainability, and machining precision. Future research should prioritize integrating AI-optimized models, real-time IoT monitoring, and innovations in sustainable materials to create more efficient and eco-friendly manufacturing processes. Figure 7a depicts ML model utilization across clusters, and a stacked bar chart shows the distribution of various ML models throughout different research fields. Figure 7b energy efficiency enhancements across clusters, a line chart demonstrating the energy savings realized in distinct clusters. Figure 7c shows sustainability effects across clusters, and a comparative bar chart illustrates the decrease in CO_2 emissions and energy use among research clusters. These visuals offer improved insight into how different technologies and approaches affect machining and manufacturing research.

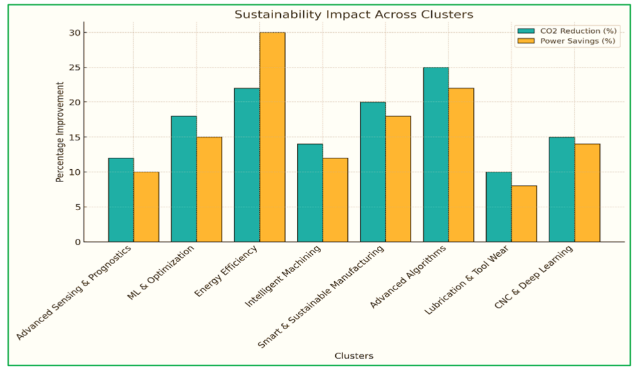
The future scope of "Energy Efficiency and Optimization Techniques" within manufacturing and machining processes is vast and promising. Emerging technologies, such as AI, ML, and digital twins, will continue to be crucial for enhancing process efficiency and reducing energy consumption. Integrating AI-driven models with real-time data from manufacturing environments enables the creation of more adaptive and responsive systems that can self-optimise under various conditions.

Furthermore, utilizing soft sensors and IoT technologies enables more detailed and real-time monitoring, which enhances decision-making processes. These advancements will support sustainable manufacturing practices by promoting energy efficiency and conserving resources. Collaboration between academia and industry is crucial for scaling up the deployment of these innovative technologies, ensuring that theoretical advancements are translated into practical applications.

The future scope of "Neural Networks and Energy Management" includes several promising directions. Enhancing the accuracy and robustness of AI models for fault diagnosis in various industrial applications remains a critical focus. Integrating more sophisticated algorithms and hybrid models could enhance predictive capabilities and reliability. In energy management, developing models that can adjust to real-time data and evolving operational conditions will be crucial. Expanding advanced deep learning architectures like 1DCNN-LSTM and densely connected CNNs could transform real-time monitoring and predictive maintenance practices. As sustainability becomes increasingly important, further research could explore AI-driven methods for



(a)



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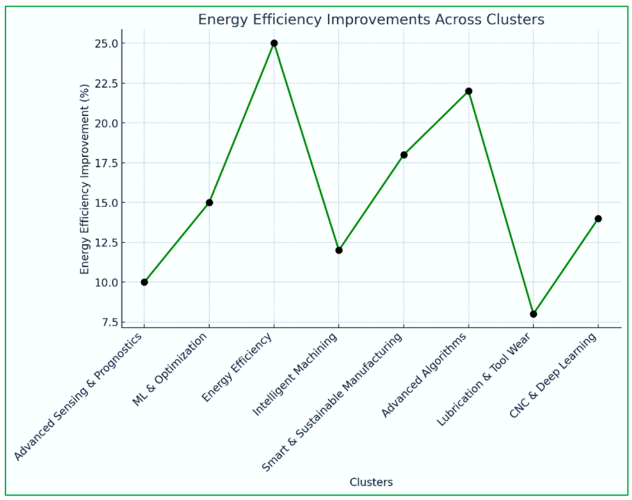


(c)

Fig. 7 **a** Cluster-wise ML models usage, **b** sustainability impact of clusters, **c** energy efficiency improvements across clusters

optimizing energy efficiency and reducing carbon footprints across diverse manufacturing processes.

3.4 Cluster 4: Intelligent Machining Processes

Cluster 4, “Intelligent Machining Processes,” demonstrates the integration of modern computing and intelligent machining methods. It focuses on energy efficiency, predictive analytics, and sustainable manufacturing using techniques such as fog computing, transfer learning, and CNN-based systems, as depicted in Fig. 8. These innovations allow real-time monitoring, autonomous process planning, and improved machining precision.

Table 5 presents studies that integrate intelligent machining processes, emphasizing energy efficiency, predictive analytics, and sustainable manufacturing. Bhinge et al. [153] developed a data-driven energy prediction model for machine tools using Gaussian process regression. Their approach enables energy-efficient process planning and optimization, suggesting the broader implementation of such data-driven models to improve energy management in machining. Shin et al. [154] focused on autonomous process planning in self-learning factories. Utilizing a hybrid learning approach combining ML and transfer learning significantly reduced energy consumption. The study highlights the ability of hybrid learning systems to enhance predictive capabilities and autonomously optimize manufacturing processes. Liang et al. [155] introduced a fog-enabled prognosis system for machining process optimization, employing convolutional neural networks (CNNs) and fog computing. Their methodology resulted in notable improvements in energy and production efficiency, demonstrating the benefits of real-time prognosis and reduced latency in machining operations. Zhou et al. [156] explored sustainable ultra-precision machining by identifying valuable two-parameter relationships through social network analysis, PCM, and k-means clustering. Their findings highlight the environmental damage and resource waste issues, advocating for

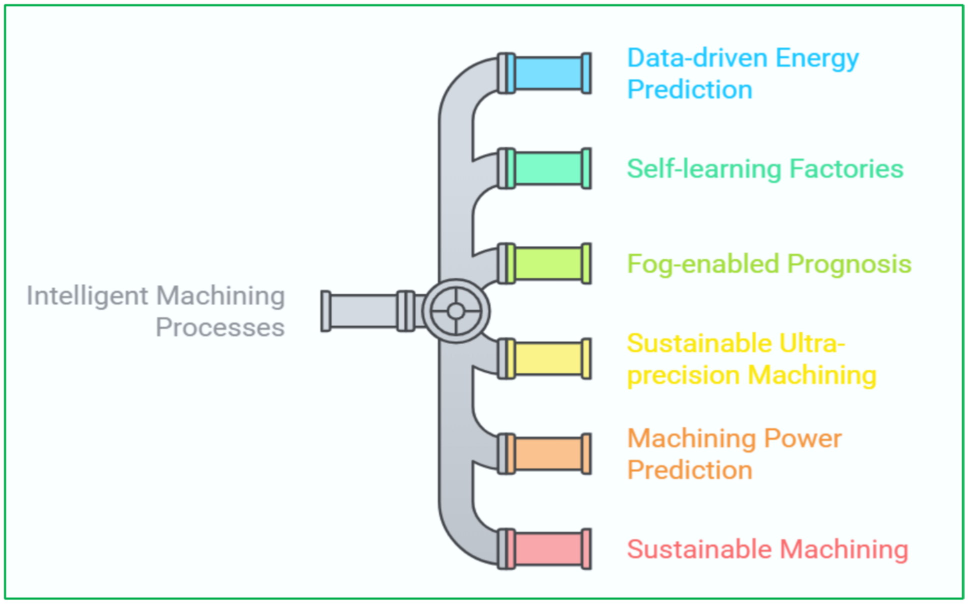


Fig. 8 Cluster 4: intelligent machining processes

using advanced analytics to uncover critical relationships and promote sustainable practices in ultra-precision machining sectors. Kim et al. [157] examined predictive models for machining power, particularly in titanium machining, using transfer learning. Their research demonstrated the effectiveness of domain adaptation in achieving accurate power predictions, which is crucial for optimizing energy consumption in machining processes.

Ross et al. [158] evaluated the environmental impacts of different cooling methods, including dry, MQL, cryogenic, and nano-based MQL, in machining Monel 400 alloy. Employing decision trees, Naive Bayes, random forests, and support vector machines, they found that nano-based MQL had the lowest carbon emissions. This study suggests that hybrid cooling methods and advanced ML models can significantly enhance sustainability metrics in machining. Korkmaz et al. [159] conducted an energy analysis for specific cutting energy (SCE) reduction in Inconel 601 machining. They used multiple linear regression, lasso regression, Bayesian ridge regression, and a voting regressor, with the Bayesian model outperforming others. Their research indicates that hybrid cooling methods hold promise for enhancing energy efficiency, supported by predictive modelling and experimental validation. Selvaraj et al. [160] focused on intelligent energy monitoring for CNC machine tools. Using a 1D-CNN-based method, they achieved high accuracy in machine state detection and feed rate prediction. These studies collectively illustrate the synergy between advanced computing and manufacturing, demonstrating how combining machine learning (ML), transfer learning, and convolutional neural networks (CNNs) with machining processes can significantly improve energy efficiency, sustainability, and predictive capabilities.

Future research based on the analysis of Clsuter 4 "Intelligent Machining Processes" could explore hybrid learning systems more deeply, integrating multiple machine learning models to enhance predictive capabilities further and optimize energy consumption in real-time. Investigating sustainable practices in ultra-precision machining can benefit from more advanced network analyses and clustering algorithms to reveal complex relationships that affect environmental sustainability. Transfer learning and domain adaptation techniques can be fine-tuned to ensure robust and reliable power predictions across various materials and machining conditions.

3.5 Cluster 5: Advanced Algorithms in Machining

Cluster 5, "Advanced Algorithms in Machining," explored advanced computational approaches to improve machining operations. Figure 9 shows innovations in surface roughness prediction, texture analysis, and optimization strategies to enhance sustainability and machining efficiency. By applying algorithms such as Genetic Programming (GP), NSGA-II, and DL models, it explores methods to optimize machining parameters, reduce power consumption, and minimize environmental impacts.

Table 6 showcased the integration of advanced algorithms in machining, emphasizing various aspects of surface roughness, texture analysis, and optimization for sustainable machining. Yesilli et al. [161] focused on automating threshold selection algorithms for analyzing surface roughness and texture. By employing information theory, signal energy, and ML, they achieved up to 95% mean accuracies and significantly reduced computational time. This indicated that automatic threshold selection algorithms could outperform

Table 5 Intelligent Machining Processes: Cluster 4

References	Research focus	Methodology	Key findings	Implications for intelligent machining processes	Recommendations
Bhinge et al. [153]	Developing a data-driven energy prediction model Data-driven approach Machine tool (Mori Seiki NVD1500	Machine Sensor Gaussian process regression	Generalized energy prediction model	Enables energy-efficient process planning and optimization	Implement data-driven models like Gaussian Process regression
Shin et al. [154]	Holonic-based mechanism for self-learning factories Self-learning factories Autonomous process planning	Hybrid learning approach combining ML and transfer learning	Achieved 9.70% reduction in energy consumption	Facilitates predictive capability Autonomous optimization in manufacturing systems	Develop hybrid learning systems that incorporate machine and transfer learning
Liang et al. [155]	Dynamic prognosis in machining process optimization	CNN-based prognosis Fog computing	Improved energy efficiency (29.25%) Production (16.50%) efficiency	Enhances efficiency Reduces latency in machining process optimization	Implement fog-enabled architectures with CNNs for real-time prognosis
Zhou et al. [156]	Identifying valuable two-parameter relationships Sustainable ultra-precision machining	Social network analysis PCM k-means clustering	Environmental damage Resource waste	Facilitates sustainable development in UPM sectors by uncovering critical relationships	Research on undiscussed relationships using advanced analytics to enhance sustainable practices
Kim et al. [157]	Predictive models for machining power Titanium machining	Transfer learning	Machining power prediction for titanium Demonstrating domain adaptation effectiveness	Accurate power prediction in machining processes Optimizing energy consumption	Implement transfer learning for machining power prediction
Ross et al. [158]	Evaluating the environmental impacts of dry, MQL, cryogenic and nano-based MQL Sustainable machining Monel 400 alloy	DT Naive Bayes RF SVM	Nano-based MQL showed lowest carbon emissions	Reduced environmental impact Improved sustainability metrics	Explore hybrid cooling methods and advanced ML models for accurate sustainability assessments
Korkmaz et al. [159]	Specific cutting energy (SCE) reduction in Inconel 601 machining Energy analysis	MLR Lasso Regression Bayesian Ridge Regression Voting Regressor	Bayesian model outperformed others Hybrid cooling methods showed promise in enhancing energy efficiency	Energy consumption in machining processes through predictive modelling Experimental validation	Implement Bayesian and hybrid cooling methods for SCE reduction in machining operations
Selvaraj et al. [160]	Intelligent energy monitoring method to assess machine states Predict feed rates based on energy consumption data	1D-CNN	95.7% accuracy in machine state detection 91.4% in feed rate prediction	Real-time monitoring Anomaly detection in ultra-precision machining processes	Implement 1D-CNN-based energy monitoring systems in CNC machines Explore further enhancements in prediction accuracy and scalability

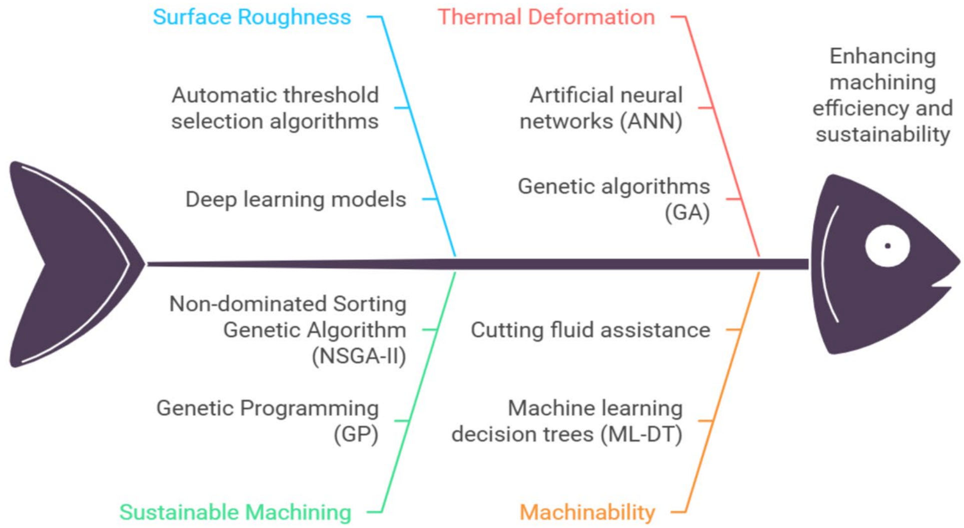


Fig. 9 Cluster 5: advanced algorithms in machining

traditional methods, suggesting their implementation could lead to more efficient surface analysis. Salem et al. [102] addressed sustainable machining through knowledge-embedded optimization using GP and the NSGA-II. Their research demonstrated improvements in surface roughness, specific energy, and unit volume machining time, highlighting that knowledge discovery approaches facilitated sustainable machining practices. This suggested that employing such optimization techniques could enhance cutting conditions and promote sustainability in machining processes. Bai et al. [162] investigated the machining of titanium alloys, aiming to predict surface roughness using DL (ResNet-50) and Maurya et al. [10] explored predicting and optimizing thermal deformation in high-speed spindles through ANN and GA. Their study achieved high prediction accuracy (R2 between 0.94 and 0.98), reduced power consumption, and reduced CO_2 emissions. Aslan et al. [163] examined the machinability of Hardox 400 in different cutting environments, focusing on enhancing machinability with machine learning decision trees (ML-DT). They found that cutting fluid assistance reduced tool wear and that machine learning models improved the understanding of machining conditions.

The future scope of Cluster 6, “Advanced Algorithms in Machining,” is promising, with numerous avenues for further research and development. Integrating ML and AI in machining processes focuses on enhancing predictive accuracy and robustness. Continued advancements in DL and feature extraction techniques could lead to more precise and reliable prediction models for surface roughness and other critical machining parameters. Developing automatic threshold selection algorithms and their implementation in real-time machining systems could revolutionize surface analysis, increasing efficiency and reducing computational costs, such as the biological swarm intelligent optimization algorithm [164]. Integrating thermal deformation prediction and optimization models into high-speed spindle operations could enhance machining precision and sustainability.

3.6 Cluster 6: Lubrication and Tool Wear Management

Cluster 6 “Lubrication and Tool Wear Management,” as shown in Fig. 10 depicts the importance of effective lubrication techniques and advanced strategies for managing tool wear, thereby optimizing machining processes. It emphasizes innovative methods to reduce friction, enhance cooling, and improve tool lifespan, ensuring sustainable and efficient manufacturing operations [165].

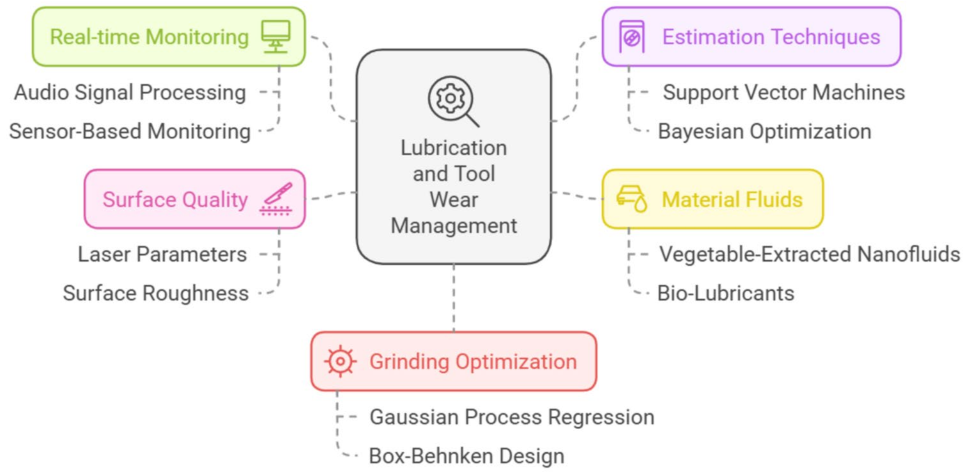
Table 7 explored various aspects of lubrication and tool wear management, employing advanced computing and machine learning techniques. Li et al. [74] investigated real-time tool wear monitoring using audio signal processing. They utilized audio sensors, blind source separation, and PCA to classify tool wear conditions accurately. Their findings suggested that audio signal processing could serve as a precise method for monitoring tool wear, recommending the deployment of audio-based tool wear monitoring systems. AI methods like SVM with Bayesian optimization significantly improved tool wear estimation accuracy, recommending their use for better predictions [166].

Ragai et al. [167] examined advanced monitoring technologies by correlating CNC turning process parameters using sensors (vibration, acoustic, current) and ML models, a quadratic discriminant analysis (QDA) classifier. They found that vibration signals were sensitive to spindle speed and power response to feed rates, with the QDA classifier achieving an accuracy of 86.9%. They concluded that combining sensor-based monitoring with ML models effectively correlated cutting conditions, recommending using

Table 6 Advanced Algorithms in Machining: Cluster 5

References	Research focus	Methodology	Key findings	Implications for advanced algorithms in machining	Recommendations
Yesilli et al. [161]	Automatic threshold selection algorithms for surface roughness and texture analysis	Information theory Signal energy ML	Mean accuracies up to 95% Reduced computational time	Automatic threshold selection algorithms can outperform traditional methods Save computational time	Develop and implement automatic threshold selection algorithms for efficient surface analysis
Salem et al. [102]	Knowledge-embedded optimization Sustainable machining	Genetic Programming (GP) Non-dominated Sorting Genetic Algorithm (NSGA-II)	Improved surface roughness Specific energy Less unit volume machining time	Knowledge discovery approaches facilitate sustainable machining	Employ knowledge discovery with GP and NSGA-II to optimize cutting conditions and enhance sustainability
Bai et al. [162]	Predicting surface roughness Machining of titanium alloys	DL (ResNet-50) Fast iterative variational mode decomposition (FI-VMD)	Improved prediction accuracy by 8.7%	DL models improve prediction accuracy Improve robustness	Utilize DL models like ResNet-50 with advanced feature extraction techniques for better prediction
Maurya et al. [10]	Predicting and optimizing thermal deformation High-speed spindles	ANN and GA	High prediction accuracy (R^2 between 0.94 to 0.98) Reduced power consumption Reduced CO2 emissions	Optimized input parameters to improve thermal deformation Sustainability in machining	Adopt ANN and GA for predicting and optimizing thermal errors in machining
Aslan et al. [163]	Enhancing machinability of Hardox 400 Different cutting environments	ML-DT	Cutting fluid assistance reduces tool wear	ML models improve understanding of machining conditions Enhance material machinability	Apply ML models to optimize cutting environments

Fig. 10 Cluster 6: lubrication and tool wear management



sensor-based monitoring with QDA classifiers. Vardhanapu et al. [168] assessed the performance of vegetable-extracted nanofluids as metalworking fluids (MWFs) in machining processes. Using an ML-based prediction model, they identified the optimal nano-MWF combination. Their findings suggested that bio-lubricants could effectively substitute petroleum-based MWFs, enhancing ecological sustainability. They recommended using ML models to determine the best nano-MWFs for improved performance. Sharma et al. [169] studied the impact of laser cutting parameters on the surface quality of aluminum alloy. They employed DNN, SVM, and optical microscopy to analyze the effects. The results showed that higher cutting speeds and lower nitrogen gas pressures significantly affected surface roughness. The study concluded that appropriate laser parameters were crucial for managing surface quality and preventing crack formation, recommending optimization of laser parameters using DNN and SVM regression. Sinha et al. [128] explored optimization in grinding, specifically the minimum quantity lubrication (MQL) grinding of Inconel 625. They applied a Box-Behnken design, RF, and GPR. Their results indicated that GPR outperformed other techniques, identifying optimal parameters for achieving low tangential force and high surface roughness. The study concluded that the MQL technique helped retain grit sharpness longer, enhancing grinding performance. They recommended using GPR for predictive modeling and optimizing MQL grinding parameters for better results.

Future research based on the analysis of Cluster 6, "Lubrication and Tool Wear Management," may further investigate the integration of advanced ML techniques and sensor technologies to improve accuracy and enable real-time monitoring. Creating hybrid models that combine various AI algorithms could enhance prediction precision and reliability. Exploring more sustainable and eco-friendlier nanofluids and bio-lubricants in machining processes may contribute to increased ecological sustainability [171]. Evaluating these advanced methods across various machining environments and materials could enhance their applicability and effectiveness.

3.7 Cluster 7: CNC and Deep Learning Applications

Cluster 7, "CNC and Deep Learning Applications," discusses how neural networks and data-driven approaches improve machining precision, automate procedures, and boost productivity. Combining real-time analytics with CNC systems enhances operational efficiency and facilitates the achievement of sustainability goals by reducing energy consumption and waste. These new methodologies enable more precise tool wear estimates, optimized cutting paths, and real-time monitoring systems. As shown in Fig. 11, through these developments, CNC technology evolves into a more intelligent and flexible framework, creating a transformational impact on the current production landscape.

Table 8 focused on various aspects of CNC machining and applied DL techniques to enhance energy efficiency, control, and process optimization. Zhang et al. [132] investigated the real-time control of CNC machine tools to improve energy efficiency and reduce carbon emissions. They utilized DBNs within an RFID-enabled environment. They found that their approach allowed for effective real-time and accurate control of CNC machines, thereby promoting energy-efficient strategies. Brillinger et al. [133] concentrated on reducing CO_2 emissions by predicting energy demand in CNC machining. They compared several methods, including decision trees (DT), random forests (RF), and boosted RF, concluding that RF provided the most accurate energy demand predictions. Their findings emphasized the potential of RF in reducing energy requirements by accurately predicting the energy demand, suggesting its practical application in energy demand prediction for CNC operations. Awan et al. [119] focused on predicting specific energy consumption (SEC) in CNC machining. They compared Gaussian process

Table 7 Lubrication and Tool Wear Management: Cluster 6

References	Research focus	Methodology	Key findings	Implications for tool wear management	Recommendations
Li et al. [74]	Real-time tool wear monitoring Tool Wear Monitoring Audio Signal Processing	Audio sensors Blind source separation PCA	Classifies tool wear conditions with high accuracy	Audio signal processing is a feasible Accurate tool wear monitoring method	Deploy audio-based tool wear monitoring
Alajmi et al. [170]	Tool wear estimation In turning process	SVM Bayesian optimization SEM analysis	SVM model with Bayesian optimization shows high accuracy Low MAPE (6.13%) Low RMSE (2.29%)	AI methods like SVM with Bayesian optimization improve tool wear estimation	Utilize SVM with Bayesian optimization to enhance tool wear estimation accuracy
Ragai et al. [167]	Correlation of CNC turning process parameters Advanced Monitoring Technologies	Sensors (vibration, acoustic, current) ML models (QDA classifier)	Vibration signals sensitive to spindle speed Power response sensitive to feed rates QDA classifier accuracy of 86.9%	Sensor-based monitoring combined with ML models for compelling correlation of cutting conditions	Use sensor-based monitoring with QDA classifier
Vardhanapu et al. [168]	Assessment of vegetable-extracted nanofluids Comparative assessment of machining performance Metalworking Fluids (MWFs)	ML-based prediction model	ML model identified the best nano-MWF combination	Bio-lubricants can be adequate substitutes for petroleum-based MWFs Improving ecological sustainability	Use ML-based prediction models to identify optimal nano-MWFs
Sharma et al. [169]	Impact of laser cutting parameters on aluminum alloy Surface Quality Cutting Speed	DNN SVM Optical microscopy	Higher cutting speed Lower nitrogen gas pressure Significantly affect surface roughness	Appropriate laser parameters crucial for managing surface quality and preventing crack formation	Optimize laser parameters using DNN and SVM regression for better surface quality
Sinha et al. [128]	MQL grinding of Inconel 625 and Optimizatio	Box-Behnken design RF Gaussian process regression GPR	GPR outperformed other techniques Optimal parameters identified for low tangential force High surface roughness	MQL technique helps retain grit sharpness longer Optimizing parameters enhances grinding performance	Use GPR for predictive modelling and optimize MQL grinding parameters

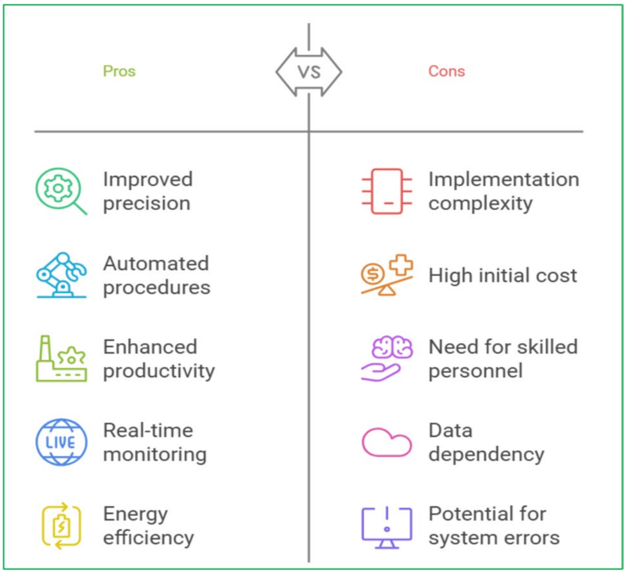


Fig. 11 Cluster 7: CNC and deep learning applications

regression (GPR), regression trees, and ANN. Their results indicated that GPR showed superior performance, achieving a correlation of 0.98 in SEC prediction. Kalandyk et al. [51] aimed to optimize spindle motion in CNC machines to enhance industrial processes. They applied DL and RL techniques, achieving higher accuracy and faster machining processes.

Enhancing CNC accuracy, automating processes, and promoting sustainability through prominent trends in DL.

- DBN and RFID-enabled CNC process optimization for energy efficiency.
- RF-based energy demand prediction models for CO_2 emission reduction.
- LSTM-based adaptive control systems for intelligent CNC operations.

The trend in ML and DL model accuracy from 2015 to 2023 is depicted in Fig. 12 and it illustrates the consistent advancement of various models, such as ANN, SVM, CNN, RNN, LSTM, GA, and ACO. DL models (CNN, LSTM, RNN) show pronounced improvements in accuracy over time. Traditional ML models (SVM, ANN) also demonstrate steady enhancements. While optimization-based methods (GA, ACO) have comparatively lower accuracy, they are still on an upward trajectory. This visualization emphasizes the increasing use and refinement of ML and DL techniques in machining, manufacturing, and predictive analytics.

The future potential of Cluster 7, "CNC and Deep Learning Applications," in the collaboration between CNC machining and DL applications is promising and diverse. As technologies evolve, further integration of deep reinforcement learning with CNC systems could lead to even greater optimization and control, improving the precision and efficiency of machining processes. Expanding RFID-enabled environments and advanced ML models like DBNs can enhance real-time control and energy management. Future research might also prioritize developing more user-friendly and cost-effective solutions to make these advanced technologies accessible to a broader range of manufacturing enterprises, thus promoting widespread adoption and advancing sustainability and efficiency objectives in the manufacturing sector.

3.8 Cluster 8: Digital Twins

Cluster 8 focuses on"Digital Twins" technologies for machining and manufacturing processes. Digital twins utilize real-time data to create virtual representations of actual machines, representing a revolutionary approach in machining and manufacturing [172]. By simulating various scenarios, these dynamic models enhance decision-making, optimize manufacturing processes, and enable predictive maintenance [173]. Digital twins provide a comprehensive understanding of machine health and operational efficiency by integrating IoT sensors with advanced analytics [174]. Besides increasing output, this technology paves the way for innovations in intelligent manufacturing [175]. Cluster 8 encompasses a broad range of innovative approaches and technologies designed to enhance precision, efficiency, and adaptability within manufacturing, refer to Table 9.

Refer to 9 for recent advancements in digital twin technologies for machining and manufacturing. It provides an organized overview of the recent literature, focusing on applying digital twin technology across various machining and manufacturing processes. [176] highlights progress in CNC machining of additively manufactured preforms, showcasing improved precision and efficiency through technologies such as structured light scanning and fused filament fabrication. This emphasis on enhancing machining precision and efficiency with digital twins continues in [177], where digital twins assist a system for fault diagnosis and utilize deep transfer learning.

[178] outlines the creation of an adaptive digital twin for machining that enhances adaptability to changing working conditions through decision models and experimental platforms. [179, 180] investigated the role of digital twins in multidimensional modeling for intelligent machining and monitoring tool and component wear, respectively, which leads to better material removal rates and reliable condition assessments. Further innovations are presented in [181], which emphasizes the development of a Clamped Adaptive Digital Twin (CADT) for blade machining, facilitating precise and effective processing of complex shapes.

Table 8 CNC machining and deep learning applications: cluster 7

References	Research focus	Methodology	Key findings	Implications for CNC	Implications for deep learning	Recommendations
Zhang et al. [132]	Energy-efficient control of CNC machine tools Energy efficiency and Real-time control	DL RFID-enabled environment DBNs	Effective real-time and accurate control of CNC machine tools, reduced carbon emissions	Real-time control Energy-efficient strategies	Use of DBNs for strategy selection	Implement an RFID-enabled environment
Brillinger et al. [133]	Prediction of energy demand CO2 emissions reduction CNC machining	DT RF Boosted RF	RF provides the most accurate energy demand predictions	Reducing energy requirements	DT and RF are effective for energy demand prediction	Use RF for accurate energy demand predictions
Awan et al. [119]	Prediction of specific energy consumption	Gaussian process regression Regression Trees ANN	GPR shows superior performance Accurate SEC prediction with a correlation of 0.98	Accurate prediction of specific energy consumption	Supervised learning techniques to predict energy consumption accurately	Use Gaussian process regression to predict specific energy consumption
Kalandyk et al. [51]	Optimization of spindle motion in CNC machines Industrial process optimization Spindle motion	DL RL	Achieved higher accuracy Faster machining process	Enhanced spindle motion optimization Improved machining speed Accuracy	Effective application of DL to replicate and enhance industrial algorithms	Use DL with RL for optimizing spindle motion

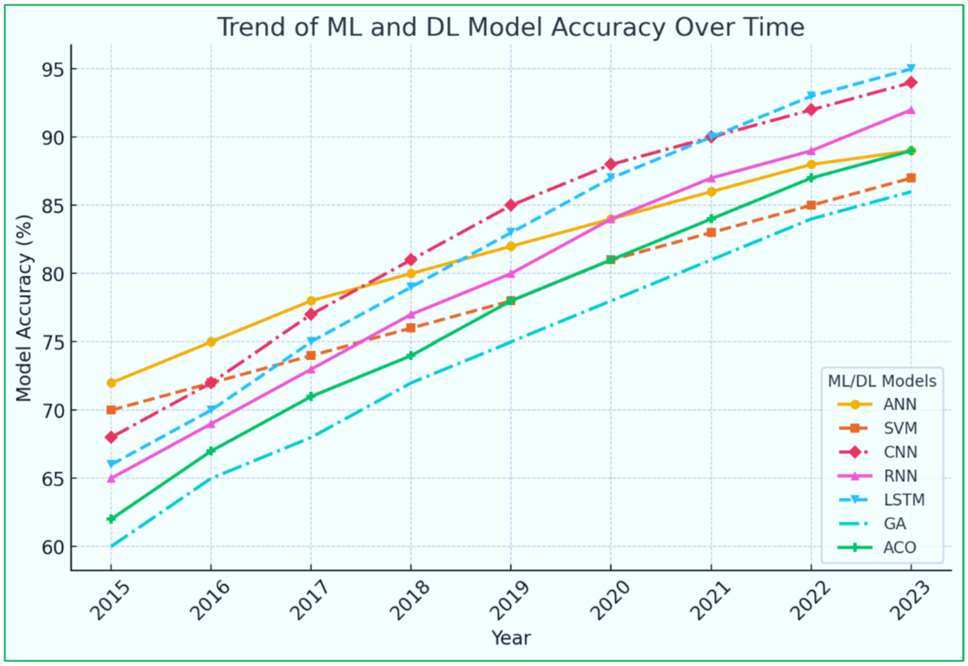


Fig. 12 Trends of ML and DL model accuracy over time

The studies [182–188] explored deeper into various applications, from monitoring tool wear in thin-walled components to advanced frameworks for CNC systems that employ large language models and improved reinforcement learning. These studies [182–188] share a common aim to enhance various facets of manufacturing through digital twins, demonstrating significant advancements in accuracy, efficiency, and adaptability. Each research effort offers a distinct perspective on addressing specific manufacturing challenges, highlighting digital twin technology's versatility and transformative potential.

While examining cluster 8, the potential for digital twins in manufacturing is significant and still largely untapped. Future research could focus on integrating real-time data analytics, IoT, and advanced AI techniques to create dynamic and responsive manufacturing environments. Furthermore, there is an opportunity to evaluate the sustainability of manufacturing processes through digital twins, aiming to reduce waste and energy consumption. The increasing sophistication of these technologies has the power to improve current manufacturing practices and to revolutionize the industry, enabling smarter, more efficient, and sustainable production methods.

4 Key Research Themes, Trends, and Comparative Analysis of Clusters

AI, ML, and DL in machining have significantly transformed traditional operations, offering efficiency, precision, and sustainability. Key research themes include advanced sensing and prognostics, focusing on real-time monitoring and predictive maintenance to reduce downtime and enhance tool wear prediction. Energy efficiency and process optimization leverage techniques such as ACO and neural networks to improve energy consumption and machining quality. The concept of digital twins enables virtual simulations to optimize processes and minimize waste, while intelligent machining processes utilize hybrid AI models for control and quality assurance. Additional research areas encompass data-driven sustainable practices and hybrid computational techniques that enhance decision-making and resource optimization. Research also emphasizes optimizing materials and machining parameters to achieve specific properties, thereby improving product quality and energy efficiency. These trends indicate a shift toward smart, sustainable manufacturing, balancing economic advantages and environmental responsibility.

AI, ML, and DL have many practical advantages in machining. The review presents various case studies and examples illustrating their effects in different machining environments. AI-driven predictive models have been shown to decrease energy usage by as much as 20%, based on recent industrial trials. These models dynamically optimize machining parameters, adjusting to material properties and tool wear variations without human input, thus enhancing machining precision and efficiency. ML algorithms have transformed tool wear monitoring, offering high levels of predictability and accuracy. This feature enables timely tool replacements, reducing downtime and ensuring consistent production quality. Implementing ML models in CNC machining has extended tool life by forecasting optimal

Table 9 Recent advances in digital twin technologies for machining/manufacturing

References	Key focus	Technologies used	Main findings	Impact on manufacturing
[176]	CNC machining of AM preforms	Structured light scanning Fused filament fabrication	Demonstrated a digital twin for CNC machining	Enhanced precision and efficiency in machining
[177]	Fault diagnosis with deep transfer learning	Big data Cloud IoT WiFi module	Proposed a digital twin-assisted fault diagnosis system	Improved accuracy and optimization of milling and drilling
[178]	Adaptive digital twin for machining	Decision models, experimental drilling platform	Adaptive reconstruction method to enhance digital twin adaptability	Increased adaptability in varying working conditions
[179]	Multidimensional modeling for intelligent machining	Digital Twin technology	Method for modeling, simulation, prediction, and control of machining processes	Improved material removal rates, reduced deformation
[180]	Monitoring tool and component wear	Tool condition codes Segmentation and classification algorithms	Novel method for monitoring and predicting wear in CNC milling machines	Robust condition determination of tool and component wear
[181]	CADT for blades	Adaptive model modification Clamped digital twin construction	Constructed a CADT to guide the finishing of the near-net-shape blade	Accurate and efficient machining of complex blade shapes
[182]	Tool wear monitoring in thin-walled parts	Domain-knowledge based monitoring, data-driven mapping	Improved tool wear recognition model Enhanced accuracy	Increased performance and reduced parameter count
[183]	Synthetic data for defect detection	Synthetic visual inspection, texture synthesis models	Developed stochastic texture models for different surface finishes	Enhanced training of visual inspection systems
[184]	Digital twin commissioning for machine tools	Scenario simulation, multi-domain modelling	Reduced commissioning time and improved machine tool performance	Faster and more accurate commissioning of machine tools
[185]	Digital twin for surface quality prediction	Vibration analysis, mathematical modeling, experimental approach	Improved prediction accuracy for surface quality using digital twin systems	Enhanced efficiency and reliability in metal cutting
[186]	Digital twin for robotic machining system	Machine learning, virtual commissioning, error analysis	Developed a DT-driven virtual commissioning system, improved machining accuracy	More precise and less cumbersome commissioning
[187]	Assembly process optimization with digital twins	Polychromatic sets, assembly deviation propagation calculations	Framework for dynamic assembly precision prediction and optimization	Improved assembly quality and consistency
[187]	Spindle thermal error modeling with digital twins	Data-mechanism fusion, multi-channel ensemble algorithm	Highly accurate thermal error prediction and compensation	Increased machining accuracy due to better error handling
[188]	Advanced digital twin framework for CNC systems	Large language models Enhanced reinforcement learning Multi-layer modeling	Reduced tool-axis vector variation rates Minimized collision incidents	Optimized CNC system performance and intelligence

cutting conditions through real-time data analysis. The combined use of AI and ML supports the implementation of predictive maintenance strategies. By examining sensor data and identifying patterns that indicate potential machine failures, these technologies help prevent costly downtime and urgent repairs. For example, AI models have been effectively utilized for anomaly detection in high-speed milling operations, enabling proactive corrective measures that significantly reduce the risk of damaging costly equipment.

4.1 Comparative Analysis of Clusters

The convergence of AI and ML in machining operations has ushered in a new manufacturing era, characterized by increased efficiency, accuracy, and flexibility. The study has prepared a comprehensive comparison matrix to fully capture the scope and depth of developments across various thematic clusters in this field. A comparative analysis of thematic clusters in AI and ML Applications in machining systematically categorizes each cluster according to its primary themes, methodologies, overlaps, and unique contributions Table (10). This comparison is essential for appreciating these clusters'distinct and interconnected roles within the broader context of smart manufacturing, refer to Table 10.

4.2 Contribution to Energy Efficiency and Sustainability

AI, ML, and DL have significantly improved energy efficiency and sustainability in machining operations. These technologies enable scientists and engineers to address challenges like high energy consumption, material waste, and environmental degradation.

- *Energy optimization in machining*: AI-driven optimization algorithms, including ACO, GA, and RL, have been widely applied to reduce energy usage while maintaining machining precision and performance. Predictive models for energy-efficient parameter settings in processes like milling and turning have significantly reduced specific energy consumption. This optimization not only lowers operational costs but also minimizes the carbon footprint of manufacturing processes.
- *Sustainable manufacturing practices*: ML models, such as RF and SVM, have been used to predict and optimize machining parameters. Precise machining techniques that minimize material waste and prevent defective outputs contribute to sustainability. Additionally, data-driven approaches using big data analytics enable real-time

Table 10 Comparative analysis of thematic clusters in AI, ML, and DL applications in machining

Cluster name	Main themes	Key methodologies	Overlaps	Unique contributions
Advanced sensing and prognostics	Real-time monitoring, predictive maintenance	SVM, CNN, RNN	Intelligent machining processes	Integration of sensory data for proactive maintenance
Machine learning and optimization in manufacturing	Optimization, predictive modeling	Genetic algorithms, ANNs	Advanced algorithms in machining	Implementation of advanced AI algorithms for optimization
Sustainability group	Energy efficiency, sustainable practices	ANFIS, ant colony optimization	Neural networks and energy management	Focus on resource conservation and energy management
Intelligent machining processes	Adaptive control systems, process automation	Deep reinforcement learning	Advanced sensing and prognostics	Adaptive systems for dynamic process adjustment
Advanced algorithms in machining	Cutting-edge computational algorithms	Machine learning techniques	Machine learning and optimization in manufacturing	Development and application of novel computational models
Lubrication and tool wear management	Tool life extension, lubrication optimization	Minimum quantity lubrication	CNC and deep learning applications	Specific focus on tool wear and lubrication management
CNC and deep learning applications	CNC machine enhancements, deep learning integrations	Deep learning models	Lubrication and tool wear management	Application of DL in enhancing CNC machine capabilities
Digital twins	Simulation and real-time mirroring of machining operations	IoT, digital twin technologies	Intelligent B machining processes, advanced algorithms in machining	Real-time simulation and operational mirroring
Neural networks and energy management	Energy management using neural networks	Neural networks, SVM	Sustainability group	Application of neural networks in managing energy use

adjustments toward energy-efficient production, effectively supporting sustainability goals [189].

- *Digital twins for resource management*: the concept of digital twins has introduced a new dimension to energy efficiency and sustainability. Digital twins simulate machining operations virtually, allowing manufacturers to experiment with various process parameters and optimize resource usage without relying on trial-and-error methods on the shop floor. This virtual-first approach significantly reduces material wastage and energy consumption during production.
- *Hybrid cooling techniques*: hybrid cooling methods have emerged as sustainable solutions, such as combining minimum quantity lubrication with cryogenic cooling. These techniques reduce the energy demands of traditional cooling systems while improving machining quality. AI models optimize the application of cooling methods, balancing energy efficiency with high-quality machining outcomes.
- *Predictive maintenance and tool management*: advanced sensing technologies integrated with AI and ML models enable predictive maintenance by accurately forecasting tool wear and machine faults [190]. This reduces unnecessary downtime and energy-intensive maintenance processes, supporting sustainability by maximizing tool lifespan and minimizing resource usage.
- *Green machining and materials optimization*: machining processes tailored to specific material properties ensure efficient removal with minimal energy input. Sustainable practices also include using renewable or biodegradable cutting fluids, further reducing the environmental impact of machining operations.

4.3 Challenges

Energy Optimization faces high computational demands, real-time adaptation difficulties, and limited scalability. Sustainable Manufacturing is hindered by the slow adoption of green materials and the high costs of implementing closed-loop systems**.** Digital Twin integration struggles with high setup costs, data integration issues, and modeling complexity. Hybrid Cooling Techniques grapple with inefficient coolant management and environmental concerns. Predictive Maintenance faces challenges in tool wear prediction accuracy and sensor integration in legacy systems. Data Utilization requires handling big data in real-time while addressing privacy and security risks. Economic Constraints include high initial costs and ROI challenges for small manufacturers. The Skill Gap arises from a lack of expertise and resistance to adopting new technologies, while Policy and Regulation issues include insufficient government support and complex regulations. Table 11 depicts key challenges in sustainable machining across various categories.

- *Data quality challenges*: Data quality poses a significant challenge in applying AI, ML, and DL in machining operations. Inaccurate models stemming from poor-quality data can be ineffective in real-world scenarios. Noise, incomplete datasets, and irrelevant features can significantly distort model outputs. In Cluster 1 (Advanced Sensing and Prognostics), integrating advanced sensors can help alleviate these challenges by providing high-fidelity data that improves the accuracy of predictive maintenance models. Sophisticated data preprocessing techniques, such as anomaly detection algorithms, offer a potential solution for cleaning data before input into learning algorithms. Robust data collection frameworks can ensure consistent data quality across various machining environments.
- *Model interpretability challenges*: Model interpretability is crucial for establishing trust and promoting adopting AI systems in various industries. Without interpretability, the implementation of AI solutions can be hindered, as users need to understand and trust model predictions to incorporate them into their production processes fully. For example, in Cluster 4 (Intelligent Machining Processes), while deep learning models deliver significant predictive advantages, their'black-box'nature often clouds the decision-making process. To tackle this issue, methods like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) can be utilized to shed light on the factors influencing the predictions of complex models. Furthermore, integrating rule-based systems that clarify decision-making logic can improve the transparency and interpretability of AI solutions in machining.

4.3.1 Cluster-Wise Contribution to Industrial Challenges in Machining

Although significant advancements have been made in utilizing AI, ML, and DL in machining processes, numerous challenges hinder these technologies'widespread adoption and optimal functioning. Scalability and computational efficiency are particularly crucial, as they determine the effective implementation of AI-driven systems in diverse manufacturing settings and across various scales. This section elaborates on these obstacles, illustrating how they arise across various thematic clusters and suggesting possible solutions to overcome them.

- Cluster 1: Advanced sensing and prognostics

  Scalability: Advanced sensing and prognostics, utilizing technologies such as acoustic emission sensors and predictive models (e.g., SVM, ANFIS), facilitate scal-

Table 11 Key Challenges in Machining and Sustainable Manufacturing

Category	Challenges	Details
Energy optimization	High computational demand	Optimization algorithms like AI and ML require significant computational power, adding overhead energy use
	Difficulty in real-time adaptation	Adapting machining parameters in real-time while ensuring energy efficiency remains challenging
	Limited scalability of models	Many optimization models work well for specific setups but struggle to scale across diverse machining environments
Sustainable manufacturing	Limited adoption of green materials	Transition to renewable or biodegradable materials in machining processes is slow due to cost and availability
	Challenges in implementing closed-loop systems	Recycling waste materials and integrating closed-loop manufacturing systems requires substantial investment
Digital twin integration	High setup and maintenance costs	Developing and maintaining accurate digital twin models involves significant upfront and ongoing costs
	Data integration challenges	Difficulty in consolidating data from various sources into a cohesive digital twin framework
	Complexity in modeling nonlinear interactions	Accurately simulating complex machining scenarios with multiple variables is a technical challenge
Hybrid cooling techniques	Inefficient cooling fluid management	Optimizing the amount and type of cooling fluids for hybrid methods without compromising energy use is difficult
	Environmental concerns of conventional coolants	Non-biodegradable coolants used in some setups contradict sustainability goals
Predictive maintenance	Accuracy of tool wear predictions	Ensuring predictive models accurately forecast tool wear under diverse machining conditions is challenging
	Integration of sensors in legacy systems	Retrofitting older machinery with advanced sensing technologies is costly and technically complex
Data utilization	Handling big data in real-time	Processing and analyzing large datasets for real-time decision-making require high-performance infrastructure
	Data privacy and security risks	Sharing sensitive operational data for cloud-based analysis poses security concerns
Economic constraints	High initial investment	Implementing AI, ML, and digital twin technologies requires substantial financial resources
	ROI challenges for small manufacturers	Smaller enterprises often struggle to justify the cost of sustainable practices due to uncertain returns on investment
Skill gap	Need for skilled workforce	Advanced machining technologies require expertise in AI, ML, and data analytics, creating a skill gap in the workforce
	Resistance to change in traditional manufacturing setups	Legacy manufacturers often resist adopting new technologies due to operational inertia and fear of disruption
Policy and regulation	Insufficient government support	The lack of incentives or subsidies for adopting sustainable machining practices slows progress
	Regulatory challenges	Complex and varying regulations across regions create obstacles to the global implementation of sustainable solutions

able machining operations by enabling predictive maintenance and real-time monitoring. This cluster enables scalability by allowing machining processes to be monitored and adjusted in real-time across various production scales, which can be seamlessly integrated into different-sized and types of manufacturing facilities.

Computational efficiency: This cluster uses efficient algorithms and models (e.g., LSTM for tool wear prediction) to reduce computational load by focusing on key predictive indicators, thus optimizing processing time and resource usage.

- Cluster 2: Machine learning and optimization in manufacturing

Scalability: It explores integrating machine learning models with manufacturing processes to enhance process control and optimization. By utilizing AI to automate decision-making processes, scalability is achieved through the consistent and efficient scaling up of operations without a proportional increase in manual monitoring and control.

Computational efficiency: ML models (such as RF and ANN) enhance the efficiency of manufacturing operations by optimizing parameters like tool paths and cutting speeds based on predictive analytics. This reduces unnecessary computational efforts and improves overall system efficiency.

- Cluster 3: Sustainability group

  Scalability: The focus on sustainability through energy management and optimization techniques, utilizing neural networks and other AI tools (e.g., ANFIS and ant colony optimization), supports scalable solutions by promoting energy-efficient practices adaptable to larger, more diverse manufacturing settings.

  Computational efficiency: Energy efficiency directly impacts computational efficiency by optimizing the energy usage of machining processes. Techniques such as evolutionary computation and ANFIS models help reduce the computational power required for process optimization.
- Cluster 4: Intelligent machining processes

  Scalability: Intelligent machining processes, utilizing CNNs and deep reinforcement learning, enable automated and adaptable machining strategies that can be applied across various machines and setups, facilitating scalability in industrial applications.

  Computational efficiency: Deep learning techniques help streamline data processing and decision-making processes, reducing the computational burden while maintaining or enhancing performance metrics such as accuracy and speed.
- Cluster 5: Advanced algorithms in machining

  Scalability: Advanced algorithms provide the groundwork for developing scalable systems that can adapt to varying demands and machining conditions without extensive reprogramming or human intervention.

  Computational Efficiency: This cluster addresses computational efficiency by enhancing algorithms for precision and speed, ensuring that machine tools operate at optimal parameters with minimal waste of computational resources.
- Cluster 6: Lubrication and tool wear management

  Scalability: Effective tool wear and lubrication management using AI techniques helps extend the life of machining tools and reduce downtime, which is crucial for cost-effectively scaling operations.

  Computational Efficiency: Predictive maintenance models and lubrication management systems optimized through AI reduce the frequency and duration of manual checks and maintenance, thereby improving the overall efficiency of machining operations.
- Cluster 7: CNC and deep learning applications

  Scalability: Integrating CNC machining with deep learning enables the creation of adaptable and scalable machining operations that can learn from experience and improve over time without requiring human intervention.

  Computational efficiency: deep learning applications streamline data processing and improve the accuracy of machining operations, reducing the need for iterative processes and manual adjustments.
- Cluster 8: Digital twins

  Scalability: Digital twins enable the virtual testing and simulation of machining processes, supporting scalability by allowing for rapid prototyping and adaptation across various production scenarios without physical trials.

  Computational efficiency: Digital twins optimize computational resources required for product development and process management by simulating various machining conditions and outcomes.

Focusing on each cluster's designated area is vital to addressing the key industrial issues of scalability and computational efficiency in machining. By incorporating these advanced technologies, industries enhance their production capabilities and navigate operational complexities more adeptly.

4.4 Practical Implications: AI, ML, and DL in Machining Operations

Numerous real-world case studies illustrate the practical applications and effects of AI, ML, and DL in machining operations. These examples from industry leaders offer concrete evidence of how intelligent systems are revolutionizing manufacturing processes.

- *General electric-predictive maintenance*: General Electric (GE) implemented the Brilliant Manufacturing Suite, leveraging machine learning (ML) to monitor factory equipment performance. By analyzing real-time sensor data, including spindle speed, vibration, and temperature from CNC machining centers used in turbine component production, GE developed predictive models to forecast tool wear and identify potential equipment failures in advance. This proactive maintenance strategy enabled early detection of issues and significantly reduced unplanned downtime by up to 30%. As a result, GE experienced a notable improvement in overall equipment effectiveness (OEE), enhancing operational efficiency and minimizing production disruptions [191].
- *Fanuc-autonomous learning robots*: Fanuc has integrated deep reinforcement learning into its industrial robots,

enabling them to learn and optimize tasks autonomously through continuous repetition. This significantly reduced the time required for the robots to adapt to new operations, minimizing downtime and enhancing flexibility across diverse manufacturing processes. Fanuc also applied deep learning techniques, CNNs, for real-time chatter and defect detection during high-speed milling. By processing acoustic and vibration signals in real-time, the system achieved an accuracy of over 95% in identifying machining anomalies. This high level of precision enabled immediate corrective actions, substantially reducing the rate of part rejections and ensuring consistent production quality [192].

- *ArcelorMittal-predictive maintenance in steel manufacturing*: by adding sensors to vital equipment to gather information on temperature, vibration, and operational characteristics, ArcelorMittal utilized ML for predictive maintenance. By using supervised learning algorithms to analyse this data, the business was able to anticipate equipment failures before they happened, which resulted in a 20% reduction in unexpected downtime and a 15% reduction in maintenance expenses [193]
- *Tata steel-enhancement of quality control*: increased scrap rates and inconsistent product quality were problems for Tata Steel. To identify patterns and anomalies in the quality data, they employed unsupervised learning techniques and monitored quality indicators, including mechanical characteristics and chemical composition, throughout the production process. With this method, the accuracy of defect identification increased by 25%, and the scrap rate decreased by 18% [194].
- *Nucor steel-process optimization*: by collecting real-time data on energy usage, manufacturing rates, and process parameters, Nucor Steel aimed to increase efficiency and reduce energy consumption. Utilising reinforcement learning algorithms to modify process parameters continuously led to a 12% gain in production efficiency and a 10% decrease in energy usage [195].
- *Manufacturer of heavy equipment-forecasting warranty claims*: Pariveda Solutions and a top-heavy equipment manufacturer worked together to create a cloud-based machine learning model that forecasts supplier-at-fault warranty claims. By examining past claims data, the model found trends that suggested provider accountability. As a result of this approach, more than $13 million worth of previously unfiled but potentially recoverable claims were identified, with a potential recovery value exceeding $7 million [196].
- *Sandvik coromant*: it has created the Machining Insights platform, which utilizes cloud-based AI analytics to track and enhance machining performance. The system captures data directly from machine tools, providing actionable information on tool usage, cycle times, and idle intervals. This allowed manufacturers to enhance machine utilisation by up to 15% while proactively identifying performance constraints [197].
- *Siemens*: to enable adaptive process control, Siemens included AI into its SINUMERIK CNC systems. These machines enhanced surface finish and tool life by dynamically adjusting cutting parameters throughout operations using reinforcement learning. This solution reduced machining cycle time and energy consumption while simultaneously improving product quality. Based on past performance data and application requirements, Kennametal unveiled an AI-powered tool selection platform that helps users select the ideal cutting tools and parameters. In the end, this improved tool management and selection efficiency by cutting down on setup time and the trial-and-error stage [198].
- *Okuma's smart factory*: its initiative showed the integration of AI across machining cells, including predictive analytics, autonomous tool condition monitoring, and real-time decision-making. Their system enabled near-autonomous machining operations, reducing human intervention while maintaining high product quality and reliability [199].

4.5 Recommendations for Researchers

- *Focus on interdisciplinary collaboration*: researchers should seek partnerships with practitioners in the fields of machine learning, engineering, and manufacturing to develop multidisciplinary solutions that address real-world challenges. Collaborations like these can help bridge the gap between theoretical research and practical application.
- *Developing standardized benchmarks*: to objectively evaluate the performance of AI models in machining applications, researchers should work towards establishing standardized benchmarks that mimic real-world manufacturing conditions.
- *Exploration of understudied areas*: areas such as the application of reinforcement learning in machining settings and the use of hybrid AI models (combining, for example, CNNs and GANs) for complex problem-solving represent fertile ground for innovative research.
- *Ethics and sustainability*: given the increasing integration of AI in critical sectors, research into the ethical implications and sustainability of AI deployments in machining is essential. This includes studies on the environmental impact of AI systems and their sustainability over long-term use.

4.6 Recommendations for Practitioners

- *Investment in AI literacy*: to effectively implement and leverage AI solutions, practitioners should invest in training programs that enhance AI literacy within their organizations. Understanding AI capabilities and limitations will enable more effective integration and troubleshooting.
- *Pilot testing*: before full-scale deployment, AI systems should be pilot tested in controlled sections of the production process to evaluate their impact on operations and identify potential areas for improvement.
- *Continuous monitoring and feedback*: AI systems are not set-and-forget solutions. Continuous monitoring and feedback mechanisms should be established to ensure these systems evolve with changing operational conditions and technological advancements.
- *Engagement with regulatory bodies*: as ai becomes more embedded in manufacturing, engaging with regulatory bodies to ensure compliance with emerging regulations and standards is crucial. This proactive approach can help mitigate risks and align AI deployments with legal and ethical standards.

4.7 Future Research Directions

AI, ML, and DL, and machining optimization studies seek to connect theoretical simulations with real-world applications. A vital focus area is validating simulation outcomes through physical experiments to confirm their applicability in CNC milling and other machining methods. Broadening DL applications to encompass more milling tasks and complex workpiece geometries will demand more excellent computational resources alongside lightweight models suitable for commercial use). Moreover, adapting DL models into production-ready solutions will require advancements in computational efficiency and reliability [57]. In addition to milling, researchers recommend investigating RF regressors across various metal removal processes, including CNC turning, end milling, and non-traditional machining techniques. Enhancing the datasets for RF models can boost their predictive accuracy while reducing the overfitting problem. Additionally, addressing the RF models'limitations, particularly their performance drop with sparse or out-of-scope data, is a priority [145]. In predicting the remaining useful life (RUL) of tools, validating the RMS value of feed force (Fy_RMS) as a critical feature across varying cutting conditions is crucial. Broadening this research to different machining processes like milling and drilling may confirm its broader applicability. Custom loss metrics can penalize instances where RUL predictions exceed actual tool life, thereby improving predictive accuracy and enhancing model precision. Furthermore, hybrid models that integrate deep learning with physics-based methods could yield more accurate estimates of tool wear [146].

In the analysis of machining time-series data, sequence models like LSTMs and GRUs show promise for predicting bending moment signals, thanks to their capability to capture long-range dependencies. Likewise, deep learning classifiers such as CNNs and ANNs require assessment for event detection in machining, although their effectiveness relies on having large datasets. Furthermore, investigating tool microgeometries can enhance machining performance by training models on various cutting tool variations [94]. Leveraging digital technologies to assess sustainability aspects, such as material footprint, economic ramifications, and environmental consequences, will enhance decision-making. Studies on energy-efficient manufacturing emphasize the importance of expanding service-oriented energy assessment systems to encompass multi-machine processing, which necessitates enhanced data integration methods [200]. In abrasive water jet (AWJ) machining, enhancing the use of artificial neural networks (ANNs) can be achieved by incorporating additional process parameters, such as abrasive types and material characteristics, to improve model generalizability. Testing ANN models on larger datasets can increase their predictive accuracy, and incorporating them into AWJ control software could enable the real-time optimization of process parameters [201]. Additionally, investigating how part orientation affects milling processes, utilizing knowledge gained from robotic repeatability studies, could lead to more accurate surface quality models. LCA methods provide a thorough environmental evaluation of CNC machining, while real-time adaptive monitoring systems can enhance efficiency by identifying machine anomalies [202].

To enhance energy-efficient machining, advancing 1D-CNN models to recognize minor variations in energy consumption can assist in detecting machine and process irregularities. Moreover, regression-based models can predict feed rates based on machine energy usage. Developing real-time platforms for identifying machine status that analyze G-code and estimate energy consumption can significantly enhance energy optimization in machining processes. Employing unsupervised learning models trained on typical operating conditions can promote early detection of anomalies, thereby reducing downtime in industrial settings [160]. Additionally, it is essential to expand research on cutting conditions and their influence on the performance of methodologies to improve anomaly detection models [203]. Generative Adversarial Networks (GANs) show potential for generating synthetic data in laser machining. This capability enables researchers to enhance limited datasets and boost training efficiency. Furthermore, GANs may also aid in predicting two-dimensional surface profiles after machining, thereby improving the accuracy of machine learning-based machining models [204, 205].

As we move towards a machine-driven future, integrating AI and ML with advanced digital fabrication technologies promises groundbreaking changes [206]. A key trend is the implementation of augmented and virtual reality systems within AI-operated machining settings [207]. These technologies will provide real-time, immersive representations of machining processes, enhanced by AI analytics to improve accuracy and decision-making [208]. This integration will boost operational precision and facilitate quick training for new operators, effectively linking digital simulations with real-world operations [209].

Another escalating trend is the application of quantum computing to tackle intricate optimization challenges in machining that are currently beyond the reach of conventional computational methods. Quantum-enhanced algorithms are expected to revolutionize the optimization of tool paths, machining parameters, and material utilization, aiming to decrease waste and energy consumption while improving output quality. As quantum computing becomes more widely adopted, its integration with ML models may lead to unprecedented levels of efficiency and innovation in machining processes [210]. The development of AI and ML will increasingly emphasize creating autonomous machining systems capable of self-repair and real-time self-diagnosis. These systems will utilize continuous learning loops to adapt to new conditions autonomously, thereby reducing operational risks and minimizing downtime. There will be an intensified focus on environmentally sustainable machining practices where AI and ML will play crucial roles in reducing energy use and emissions, aligning with global sustainability goals [138].

Integration with Industry 4.0: integrating AI, ML, and DL with Industry 4.0 represents a significant frontier for enhancing machining operations. Future studies should focus on the seamless integration of these technologies with the Internet of Things (IoT), cyber-physical systems, and big data analytics, which form the foundation of Industry 4.0. For instance, AI-enhanced predictive maintenance systems could benefit from IoT devices that constantly gather operational data from machining equipment. This integration enables real-time data evaluation and informed decision-making, improving operational efficiency and reducing downtime.

A potential research avenue could involve creating standardized Application Programming Interfaces (APIs) to simplify the integration of AI models with existing Industry 4.0 frameworks. Another promising field is establishing security protocols to protect the data shared between AI systems and Industry 4.0 networks, thus ensuring the integrity and confidentiality of sensitive industrial information.

Advancing with digital twins: digital Twins are virtual representations of physical systems that create a safe environment for testing AI algorithms, eliminating the risk of damaging actual machinery. In machining, Digital Twins can significantly accelerate the development and testing of AI models by simulating various manufacturing scenarios and their associated effects. Future research should investigate how to integrate Digital Twins with cutting-edge AI methods to predict failures, streamline processes, and enhance product quality. A potential research avenue could involve creating advanced simulation models that integrate real-time data from the production line to update and refine the Digital Twin continuously. This ensures that the Digital Twin accurately mirrors the current condition of the physical system, enabling more precise predictions and assessments. Furthermore, research could explore the application of Digital Twins for training AI systems in a secure virtual setting before their actual deployment, which could lower both the time and costs involved in introducing AI advancements to the market.

Explainable AI (XAI) in machining: explainable AI (XAI) aims to address a key shortcoming of contemporary AI systems: their lack of transparency in decision-making processes. In machining, where precision and dependability are crucial, XAI can significantly enhance the clarity of AI-driven decisions for human operators. Future research may focus on creating XAI frameworks that render complex models, such as deep learning networks used for predictive maintenance and process optimization, more interpretable. Practical applications may involve visual explanations of model decisions, such as highlighting features in sensor data that contribute to specific predictions, thereby enhancing trust and simplifying troubleshooting and maintenance.

Federated learning for machining processes: federated learning represents a revolutionary approach to utilizing data for training AI models. It facilitates the development of collective machine learning models without the need to transfer extensive data to a central server, thereby effectively resolving significant data privacy and security issues in sensitive manufacturing settings. In machining, federated learning may enable manufacturers to leverage shared predictive models developed from multiple facilities while maintaining data security. Future research could focus on evaluating the effectiveness of federated learning in improving supply chain logistics and production scheduling across manufacturing units situated in various geographical areas.

Future research in machining and deep learning optimization encompasses several areas, including validating physical simulations, developing hybrid models, addressing sustainability concerns, and detecting anomalies in real-time. Closing these research gaps will lead to major developments in CNC machining, industrial automation, and AI-enhanced process optimization, resulting in more efficient, sustainable, and precise manufacturing systems.

5 Conclusions

This study offers a systematic review of AI, ML, and DL applications in machining, highlighting their impact on enhancing energy efficiency, sustainability, and precision. It compiled 182 research articles from the Scopus database and organized them into eight thematic clusters based on author keywords. Each cluster's critical review examined significant trends, advancements, and challenges associated with AI-driven machining strategies. The systematic review identifies the significant contributions as follows.

In *'Advanced Sensing and Prognostics,'* AI models, including LSTM and RNN, have exceeded 90% accuracy in predicting tool wear and facilitating real-time monitoring. The use of acoustic emission sensors, alongside audio signal processing, has advanced non-intrusive monitoring of tool conditions. Deep learning methods, such as CNNs and ANNs, have significantly enhanced defect detection and stability in machining processes. In *'Machine Learning and Optimization in Manufacturing,'* implementing techniques such as RF, SVM, and GA has refined machining parameters, yielding a 10–25% decrease in energy use. The application of hybrid AI, which includes DRL and transfer learning, has further enhanced efficiency and stability in processes. Moreover, ML-driven predictive analytics have achieved over 95% accuracy in predicting surface roughness, leading to improved product quality and reduced waste. *'Energy Efficiency and Optimization Techniques'* remain a prominent area of research, with AI-based process planning and scheduling models enhancing energy efficiency by 15–30%. Optimization strategies like PSO, ACO, and hybrid DL methods have effectively reduced energy consumption in CNC machining. Furthermore, incorporating digital twins has allowed for real-time monitoring and adaptive energy management, contributing to more sustainable machining operations.

In the *'Intelligent Machining Processes,'* cluster AI-driven fog computing and CNN-powered prognosis systems have transformed real-time machining control. Using hybrid learning models for autonomous process planning has resulted in a 9.7% decrease in energy consumption within self-learning factories. Also, intelligent cooling methods such as Minimum Quantity Lubrication (MQL), cryogenic cooling, and hybrid approaches have greatly diminished carbon emissions and machining costs, promoting sustainable manufacturing practices. *'Smart and Sustainable Manufacturing'* has gained from AI, ML, and DL-obsessed sustainability modeling, achieving a 12% to 44% reduction in CO_2 emissions during machining processes. Smart manufacturing frameworks enabled by digital twins have enhanced decision-making, process optimization, and predictive maintenance. Moreover, neural networks and evolutionary algorithms have improved machining precision and sustainability. In"Advanced Algorithms in Machining,"CNC machining optimization has been achieved through deep reinforcement learning (DRL), resulting in greater precision and extended tool life. Adaptive control algorithms have reduced rework rates, while hybrid AI models that merge reinforcement learning and traditional machining practices have significantly increased process adaptability.

In *'Lubrication and Tool Wear Management,'* AI-enhanced nano-lubrication methods, such as nanofluids and MQL, have reduced machining tool wear and energy usage by as much as 20%. Machine learning-based strategies for lubrication have enhanced predictive monitoring of tool wear, and AI-supported cooling and lubrication techniques have diminished machining friction and prolonged tool life. For *'CNC and Deep Learning Applications,'* techniques like CNNs, RNNs, and transfer learning have improved accuracy and defect detection in CNC machining. AI-powered chatter detection systems have stabilized CNC machining, decreasing tool damage and less production downtime. Additionally, neural networks have optimized CNC path planning and energy-efficient machining, resulting in improved resource utilization. *'Neural Networks and Energy Management'* have been essential in optimizing energy usage during machining. AI models, including ANN, LSTM, and SVM, have enhanced predictive accuracy to over 93%. AI-driven load balancing and energy-efficient scheduling models have lessened power consumption in machining, while multi-objective optimization algorithms have improved the sustainability of CNC machining.

The analysis of different clusters reveals that Machine Learning and Optimization are the most frequently utilized techniques in AI-driven machining. Meanwhile, Energy Efficiency and Optimization has shown the most significant impact on sustainability. Deep learning-based real-time monitoring has significantly enhanced tool life, process control, and defect detection across the machining industry. However, the study highlights challenges such as data quality, model interpretability, and computational scalability, which hinder the full-scale industrial adoption of AI-driven machining.

This systematic review thoroughly examines the roles of AI, ML, and DL in machining operations, highlighting significant advancements while identifying ongoing challenges. By organizing the substantial literature into clear thematic clusters, this study clarifies the current landscape and outlines a comprehensive roadmap for future research and development.

The review acts as a vital link between academic research and industrial practices. It translates complex theoretical ideas into practical, actionable insights that can be effectively utilized in industrial environments. For example, discussions on advanced sensing and prognostics demonstrate how AI can enhance predictive maintenance strategies, thereby minimizing downtime and increasing efficiency in real-world manufacturing settings. Similarly, the analysis of digital twins and federated learning demonstrates how these innovative technologies can be applied to develop more agile and responsive manufacturing processes. Furthermore, the review addresses key industrial challenges, including improving computational efficiency, ensuring scalability, and enhancing data security, which are crucial for the effective integration of AI technologies in manufacturing. By providing specific examples and potential solutions to these issues, the review advances academic understanding while delivering practical benefits to industry stakeholders aiming for successful AI implementation.

This systematic review consolidates leading research on AI, ML, and DL applications in machining, serving as a valuable resource for both scholars and industry professionals. It supports the progression of academic inquiry while facilitating the practical application of cutting-edge technologies in machining operations, thereby helping to bridge the gap between research and real-world implementation and promoting a more cohesive approach to intelligent manufacturing. Future research should focus on developing real-time, adaptable AI models for machining process management, enhancing AI-powered energy efficiency strategies through hybrid optimization methods, and expanding the application of AI-driven Digital Twin technologies in smart manufacturing. Additionally, merging IoT, AI, and predictive analytics can improve manufacturing sustainability, efficiency, and precision. This systematic review establishes a clear framework for connecting academic research with industrial applications, paving the way for AI-driven smart manufacturing and Industry 4.0.

Several significant limitations are identified by the systematic review on integrating AI and ML in machining processes. These include problems with data quality that affect the precision and applicability of models, challenges with model interpretability and scalability that impede their integration into current systems, computational limitations that restrict the real-time application of these models, and a fragmentation of research that concentrates too narrowly on particular machining types or materials without taking a comprehensive approach. These difficulties point to important directions for further study, especially in improving AI models'scalability, resilience, and real-time efficiency in the machining industry.

The systematic review's methodology in integrating AI, ML, and DL in machining processes has various limitations that can influence the stringency of its findings. To begin with, the review limits its literature sources to the Scopus database, and thus it can introduce selection bias by excluding studies from other pertinent databases. Furthermore, limiting included studies to those published in English excludes significant research in other languages, which might yield interesting information. The approach depends on abstract and conclusion-only screening, which might exclude studies of interest where important information is outlined in the full texts, thereby compromising the thoroughness of the review. Such methodological decisions, although convenient in terms of controlling scope, can restrict the findings'depth, breadth, and usability.

Acknowledgements Not applicable.

Author Contribution Rupinder Kaur: Conceptualization of the study, systematic literature review, data collection from the Scopus database, cluster formation using VOSviewer, critical analysis of AI, ML, and DL applications in machining, manuscript writing, and final editing.; Raman Kumar: Supervision, methodological validation, research framework design, technical insights into AI-driven machining strategies, energy optimization techniques, and contributions to the discussion and interpretation of results.; Himanshu Aggarwal: Review and refinement of computational methodologies, providing expertise in automated models for CNC machine tools, cross-validation of research findings, ensuring the integration of AI and ML concepts in machining applications, and manuscript revision. All authors have read, reviewed, and approved the final manuscript for submission.

Availability of Data and Materials All data generated or analyzed during this study are included in this published article.

Declarations

Conflict of Interest The authors declare no competing interests.

Ethical Approval and Consent to Participate No animals were experimented for this study.

Consent to Publication Not applicable.

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