Review

The role of artificial intelligence and machine learning in mechanical engineering: A review

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ABSTRACT

This paper presents a review of the role of artificial intelligence (AI) and machine learning (ML) in advancing mechanical engineering, with an emphasis on domain-specific implementations that have driven recent technological progress. Applications such as predictive maintenance, structural integrity assessment, intelligent design optimization, automated quality inspection, and renewable energy system enhancement demonstrate the capacity of AI approaches, including deep neural networks and reinforcement learning, to improve performance efficiency, minimize operational costs, and foster sustainable engineering solutions. Beyond individual applications, the review discusses fundamental AI attributes, including model adaptability, interpretability, and the coupling of data-driven techniques with physics-informed frameworks, which collectively enable scalable adoption across mechanical engineering disciplines. Notwithstanding these advances, unresolved issues persist, particularly in terms of model reliability, computational overhead, and the availability of high-quality data. By consolidating recent research outcomes, highlighting existing limitations, and proposing prospective research pathways, this review aims to provide valuable insights for both academic researchers and industry.

Keywords: Artificial intelligence; Machine learning; Industry 4.0; Mechanical engineering.

1. INTRODUCTION

The fourth industrial revolution has provided a strong impetus for the integration of advanced digital technologies into traditional engineering domains, thereby fundamentally transforming the ways mechanical systems are designed, operated, and optimized [1, 2]. Among the core technologies, AI and ML have increasingly attracted widespread attention due to their ability to enhance automation, support intelligent decision-making, and improve the operational performance of industrial systems [3]. AI aims to develop information-processing systems capable of performing tasks that require human-like cognitive functions and of learning directly from their own operational data [4].

Numerous review studies have examined the application of AI and ML within specific subdomains of mechanical engineering. Nevertheless, there remains a clear demand for a holistic review that synthesizes advancements across multiple areas and addresses cross-cutting challenges affecting the discipline as a whole. Existing literature largely lacks an integrated perspective that simultaneously considers concerns associated with large-scale AI adoption, model transparency, and effective data integration strategies. Recent research has introduced adaptive and hybrid modeling approaches that significantly enhance predictive maintenance capabilities, thereby extending the role of AI and ML beyond their conventional use cases. Traditionally, maintenance strategies have relied on either scheduled preventive approaches, often disconnected from actual equipment condition, or reactive methods that respond only after system failures occur. In contrast, predictive maintenance leverages real-time data and advanced analytical algorithms to anticipate potential failures before they happen, leading to extended equipment lifespan, reduced downtime, and substantial cost savings through timely maintenance actions [5]. For instance, machine learning techniques can analyze sensor-generated operational data to detect patterns and anomalies that precede mechanical faults, enabling proactive maintenance decisions [6].

Unlike earlier reviews, this study offers a broad and integrative assessment of AI and ML applications across multiple domains of mechanical engineering, while providing an in-depth discussion of emerging AI paradigms, including transformer architectures and large language models (LLMs). The review differentiates itself by systematically linking domain-specific innovations with overarching technical challenges and prospective research directions. Recent studies indicate that AI and ML-driven approaches are reshaping mechanical engineering practices by enhancing predictive maintenance strategies, advancing design optimization, improving robotic and automated systems, and ensuring structural reliability [7]. Through these capabilities, AI and ML contribute to increased operational efficiency, foster innovation, and promote sustainable engineering solutions. Moreover, these technologies enable engineers to address complex engineering problems with greater speed and flexibility, facilitating breakthroughs that were previously unattainable. Given the rapid integration of AI and ML into mechanical engineering workflows, a review is essential to fully understand their transformative potential. Accordingly, this review aims to consolidate recent developments, identify critical challenges, and outline emerging trends that will shape future research in the field.

AI and ML methods offer significant advantages in industrial applications, particularly for automated mechanical systems in which the degree of automation plays a decisive role. This automation process relies primarily on data transmission and processing systems built upon electrical–electronic infrastructures. However, the transmission and processing of large amounts of information are often accompanied by various challenges (figure 1), as highlighted in recent studies [8]. Undefined errors may arise throughout the data transmission and processing chain, severely affecting the efficiency and reliability of the system. These issues mainly stem from the inherent uncertainties of electromechanical systems, which make it increasingly difficult to maintain stability, accuracy, and dependability. In this context, the application of AI-based techniques in data analysis and processing is regarded as a promising solution for optimizing operational workflows, mitigating risks, and enhancing the performance of automated manufacturing systems.

Figure 1. *Schematic illustration of the major challenges associated with the implementation of AI and ML.*

AI technologies enable the monitoring and assessment of the stability of information systems during data transmission, thereby ensuring the safety and accuracy of both input and output signals. With their ability to perceive the operational environment, perform rapid data analysis, and address complex problems in real time, AI systems not only enhance the efficiency of data processing but also optimize mechanical manufacturing workflows and automated systems [4, 9, 10]. The integration of AI into the production chain enhances monitoring, prediction, error mitigation, cost optimization, and resource efficiency, thereby improving product quality and competitiveness while simultaneously promoting sustainable development within the industrial sector.

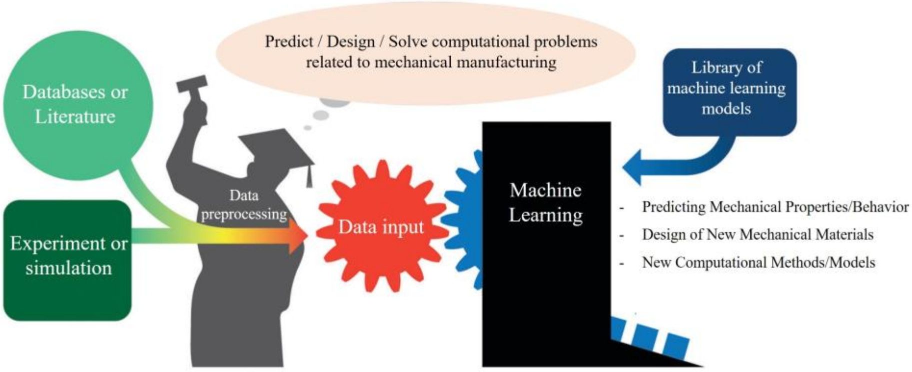

Figure 2. *Typical workflow for machine learning based mechanical design.*

This paper reviews the development of research on AI and ML applications in mechanical engineering and proposes a general framework for ML-based studies. As illustrated in figure 2, the workflow for integrating ML into mechanical problems comprises three core components: (i) a well structured dataset, collected from databases, existing literature, or generated through experiments and simulations; (ii) an ML model capable of learning from and exploiting data representations to address specific tasks; and (iii) a clearly defined mechanical research problem that has not been effectively solved using traditional methods or whose performance can be enhanced through ML. The synchronized combination of these three components is a prerequisite for advancing ML-based research in mechanical engineering.

2. AI AND ML

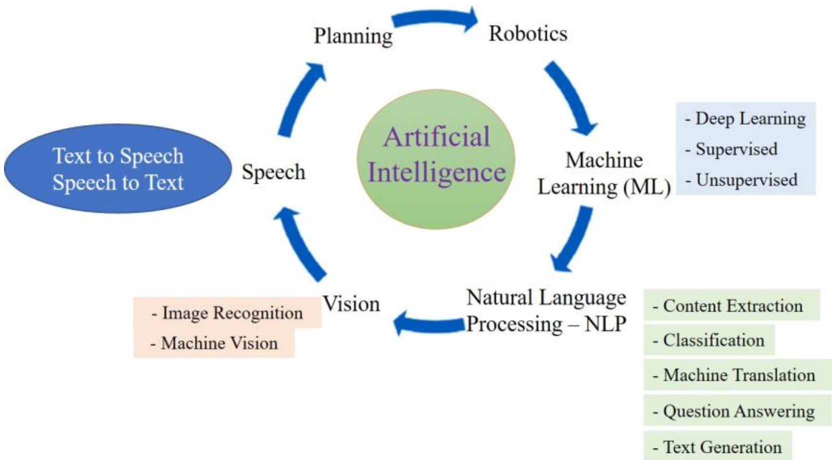

Figure 3. *Diagram illustrating Tesla's Autopilot system employing AI and ML algorithms [11].*

AI is emerging as a pioneering technology in computer science, aiming to investigate the nature of intelligence and develop systems that simulate human-like reasoning through methods such as virtual reality, simulation, and speech recognition. AI has evolved through several stages: from intelligent computing, to perceptive intelligence, and currently to cognitive intelligence. During the computing stage, computer systems are capable of performing calculations and presenting information in a manner analogous to humans. Moving further, in the perceptual intelligence stage, robots can not only recognize images, speech, and language but also make decisions based on the perceived information. Today, with the advancement of cognitive intelligence, machines are able to think and act like humans, exemplified in applications such as autonomous vehicles and automated robot products predominantly developed within the field of machine learning [10]. For example, Tesla's Autopilot system employs AI algorithms to adjust vehicle behavior under various driving conditions. The system utilizes neural networks trained on large volumes of real-world driving data to make decisions regarding braking, acceleration, and steering [11] (as shown in figure 3).

ML methods can be categorized into three main groups: supervised learning, unsupervised learning, and reinforcement learning (figure 4). Supervised learning is a task-oriented approach that optimizes the mapping from inputs to outputs based on labeled data (ground truth). In contrast, unsupervised learning is a data-oriented approach that extracts hidden structures or patterns from unlabeled data.

Reinforcement Learning (RL) fundamentally differs from supervised and unsupervised learning, primarily because it does not rely on labeled data. RL focuses on the interaction between an agent and its environment. While supervised and unsupervised methods optimize a loss or objective function to evaluate model performance, RL aims to maximize the cumulative reward obtained from the agent's actions.

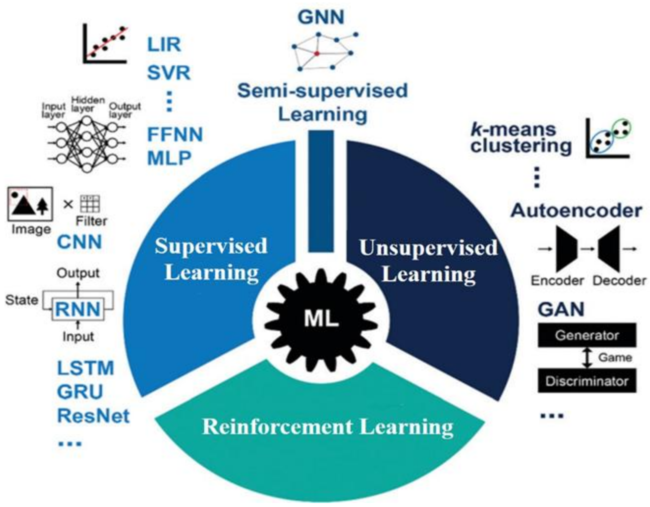

Figure 4. *Overview illustration of ML methods.*

3. APPLICATIONS OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN MECHANICAL MANUFACTURING

The mechanical manufacturing sector has entered the Fourth Industrial Revolution, characterized by the robust integration of advanced technologies such as the Internet, Big Data, the Internet of Things (IoT), and AI into production processes. This integration has been driving profound changes in manufacturing approaches, aiming toward a smarter and more flexible production environment [3, 12]. In recent years, numerous significant studies have been conducted to integrate and apply these principles to future industrial production systems [13].

The application of AI and ML in predictive maintenance has enabled the early forecasting of failures, allowing timely and precise intervention in system maintenance. Unlike traditional maintenance approaches, predictive maintenance optimizes the upkeep process by anticipating potential issues rather than following fixed schedules or intervening only after a failure occurs.

Specifically, preventive maintenance (figure 5) is performed according to a predetermined schedule without considering the actual condition of the equipment, whereas reactive maintenance is carried out only after a failure has occurred, causing production disruptions.

Data collection and preprocessing

Predictive maintenance relies on the continuous collection and analysis of data from sensors integrated within mechanical systems, monitoring key attributes such as temperature, vibration, pressure, and acoustic signals. To ensure high-quality input data for AI and ML algorithms, preprocessing is essential, including feature extraction, normalization, and dimensionality reduction. Feature extraction identifies the most relevant factors from raw data, normalization ensures a consistent value range across features, and dimensionality reduction decreases model complexity while retaining critical information. These steps optimize the performance and accuracy of predictive models, enhancing the detection of potential faults in mechanical systems [14].

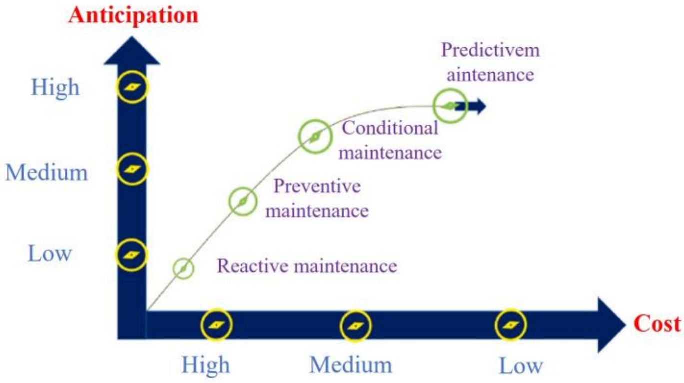

Figure 5. *Comparative diagram of preventive, reactive, and predictive maintenance strategies. machine learning models for predictive maintenance systems.*

Regression Analysis: Methods include polynomial regression and linear regression. These models estimate the relationship between sensor data and the time to failure, providing a temporal framework for maintenance activities [13].

Artificial Neural Networks (ANNs): Predictive maintenance can be significantly enhanced using ANNs [8], particularly, deep learning models such as recurrent neural networks (RNNs) [13] and convolutional neural networks (CNNs) [15]. RNNs are well-suited for time-series data, making them ideal for sensor signal analysis, whereas CNNs are effective for processing spatial data, such as visual inspection images. These models are capable of recognizing complex patterns and providing accurate predictions of equipment conditions [8, 9].

Random Forests and Decision Trees: Tree-based models, such as Random Forests, are highly favored due to their robustness and interpretability. These models can handle various types of sensor input data, as they are capable of processing both numerical and categorical data. To minimize overfitting and enhance predictive accuracy, they construct an ensemble of decision trees [16].

Support Vector Machines (SVMs): SVMs are highly effective for classification tasks, such as determining whether a device is malfunctioning or operating normally. When dealing with high-dimensional data, SVMs play a crucial role in developing predictive models by accurately distinguishing between normal and abnormal conditions. SVM models can optimize the classification space to make precise decisions even in complex data scenarios, making them an ideal tool for predictive maintenance applications [17].

Clustering Methods: Algorithms such as DBSCAN and K-means are used to group sensor data and identify similar patterns. These algorithms facilitate the detection of anomalous patterns that deviate from normal data, thereby highlighting potential issues. DBSCAN, with its capability to identify high-density clusters, and K-means, with its high clustering efficiency, both play important roles in detecting abnormal patterns within industrial systems [18].

Implementation of predictive maintenance systems

The implementation of predictive maintenance involves several key steps, as illustrated in figure 6. The described predictive maintenance framework presents a comprehensive, data-driven strategy for enhancing equipment reliability. Continuous monitoring through sensors and data acquisition devices enables real-time collection of critical system parameters, which are centralized in a database to ensure consistency, integrity, and accessibility of large-scale datasets. Historical failure records and associated indicators are used to train and validate ML models, ensuring predictive accuracy and generalizability to new operational conditions. Deployment of validated models facilitates real-time analysis and timely alerts, supporting proactive interventions before failures occur. Moreover, integrating predictive insights into maintenance decision-making allows for optimized scheduling based on estimated time-to-failure, reducing unplanned downtime and improving resource utilization. This multi-step approach highlights the synergy between advanced analytics, robust data management, and operational integration, demonstrating the potential of predictive maintenance to improve both reliability and efficiency in industrial systems.

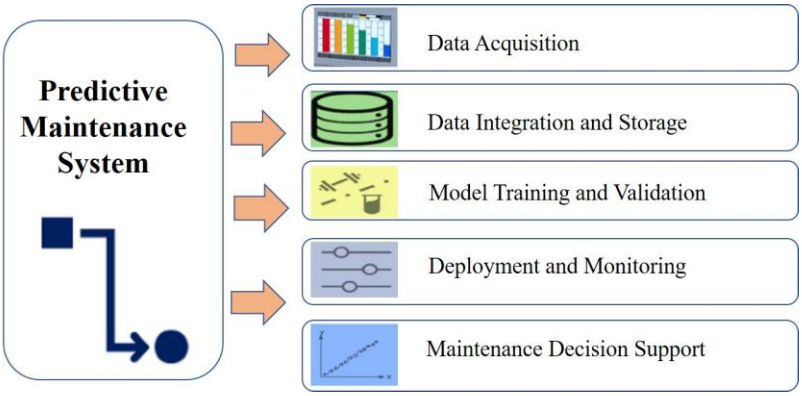

Figure 6. *Implementation of a predictive maintenance system.*

4. MECHANICAL DESIGN OPTIMIZATION TECHNIQUES USING AI AND ML

Design optimization is a fundamental aspect of mechanical engineering, focusing on the determination of optimal parameter sets that achieve targeted performance objectives while satisfying imposed constraints. The adoption of AI and ML has substantially transformed this process by enabling efficient exploration of high-dimensional design spaces and accelerating the identification of near optimal solutions. Through their capability to learn complex relationships between design variables and performance metrics, AI- and ML-based approaches enhance the effectiveness of key stages in the design optimization workflow [8, 9]. There are some key optimization techniques in mechanical design that are enhanced by AI and ML. Genetic Algorithms (GAs) are population-based optimization methods inspired by natural selection. They evolve candidate solutions represented as sets of design parameters through iterative selection, crossover, and mutation, converging toward optimal designs that satisfy performance criteria and design constraints [19]. Neural networks, particularly deep learning models, facilitate data-driven design optimization by learning complex patterns from historical data, enabling generative design, pattern recognition, and image-based optimization that can surpass conventional methods [15]. Evolutionary Strategies (ES) similarly generate and evaluate candidate solutions but employ elitism, recombination, and mutation to efficiently explore high-dimensional or chaotic design spaces[20]. RL enables agents to learn optimal policies through trial-and-error interactions with dynamic environments, proving effective in sequential and uncertain decision making tasks [21]. Bayesian Optimization (BO) utilizes probabilistic surrogate modeling to guide searches in resource-intensive or time-consuming evaluations, focusing on regions with high potential for improvement [22]. Swarm Intelligence (SI) methods, such as Particle Swarm Optimization and Ant Colony Optimization, leverage collaborative behaviors among agents to navigate multimodal, nonlinear, or discontinuous design spaces [23]. Finally, metaheuristic algorithms, including Harmony Search, Tabu Search, and Simulated Annealing, iteratively explore complex solution spaces and are often combined with AI techniques to enhance scalability and optimization performance [24]. For example, through interactions with a simulated environment (figure 7), the reinforcement learning agent successfully learned optimal wing designs. The application of this approach allowed the manufacturer to identify innovative wing configurations that markedly reduced both fuel consumption and aerodynamic drag compared with traditional designs [25].

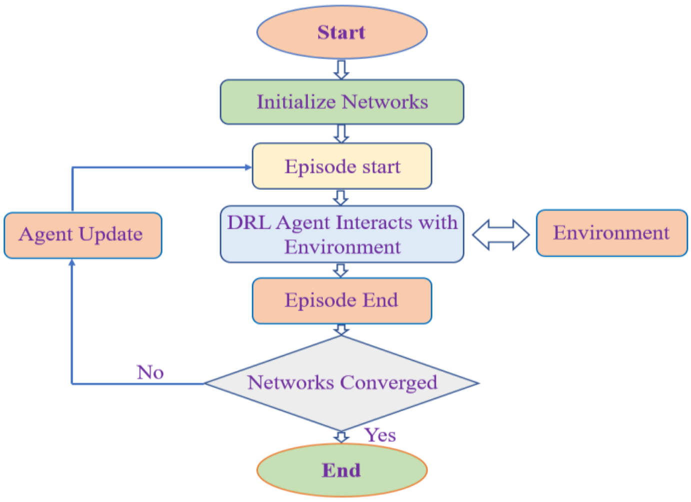

Figure 7. *Schematic of an aircraft wing illustrating the optimized design parameters obtained using reinforcement learning [25].*

AI and ML-driven optimization approaches have substantially enhanced both the efficiency and robustness of mechanical engineering design processes. By leveraging techniques such as genetic algorithms, neural networks, evolutionary and reinforcement learning strategies, Bayesian optimization, swarm intelligence, and other metaheuristic methods, engineers are able to address complex design optimization challenges and develop solutions that effectively satisfy performance objectives and design constraints.

5. OPTIMIZATION OF MANUFACTURING PROCESSES THROUGH AI AND ML

In recent years, AI and ML have driven significant advancements in manufacturing processes, including additive manufacturing, machining, and quality control, by enhancing efficiency, productivity, and product quality. Machine learning algorithms analyze large datasets from sensors and monitoring systems to forecast, optimize processes, detect defects early, and reduce resource waste.

In additive manufacturing, AI and ML support design optimization to minimize material usage, create lightweight and efficient structures, and improve print quality. They also optimize process parameters such as temperature, speed, and layer thickness through equipment data analysis, while computer vision is applied to detect defects such as surface irregularities, voids, or warping, enabling timely intervention and ensuring product consistency [26].

In machining, ML models predict tool wear based on sensor data and process parameters, enabling optimization of tool lifespan and proactive replacement strategies. AI is also used to optimize tool paths, improve surface quality, reduce energy consumption, and shorten cycle times. ML-based monitoring systems continuously detect anomalies and deviations, allowing real-time adjustments to enhance machining efficiency and accuracy [27].

In quality control, computer vision and ML systems automatically detect surface defects, dimensional deviations, and assembly errors through image or 3D scan analysis. ML is further applied to monitor process variability, analyze root causes of quality issues, and implement proactive control measures. Predictive models for equipment failure and maintenance requirements help prevent downtime, improve reliability, and optimize overall operational efficiency [27].

6. CHALLENGES AND FUTURE OF AI AND ML IN MECHANICAL ENGINEERING

Future research on AI and ML in mechanical engineering will focus on integrating physics-based models with data-driven approaches to enhance interpretability and predictive capability. Another prominent direction is the application of AI for sustainable design, where optimization techniques are employed to reduce resource consumption while maintaining product performance.

Despite their potential, AI and ML face several challenges in mechanical engineering. Data quality and completeness remain major barriers, as noise, missing values, and biases in experimental datasets can degrade model performance, particularly in specialized applications or emerging technologies with limited data. Moreover, labeling data for supervised learning tasks is often time-consuming and costly, requiring substantial human resources [12, 14]. The high complexity and computational demands of advanced AI models present additional obstacles. Applications such as predictive maintenance and design optimization require the management of large, high-dimensional datasets, necessitating high-performance computing infrastructures, including clusters or specialized hardware. The expansive parameter space of complex ML architectures, such as deep neural networks, further increases training time and resource requirements.

Depending on system complexity, data infrastructure, and computational demands, the financial investment for AI deployment in mechanical engineering varies. Model robustness and generalizability are also critical concerns, as models trained on specific datasets often underperform in diverse environments or unseen conditions. Additionally, AI models are vulnerable to adversarial attacks, where small, intentional perturbations can cause erroneous predictions or classifications, posing risks in safety-critical applications. Large-scale AI deployment requires substantial financial investment, particularly in high-performance computing infrastructure and skilled personnel, which may be a barrier for small and medium-sized enterprises. Integration of AI also faces challenges due to compatibility issues and the need to upgrade legacy systems, as many current mechanical devices rely on outdated hardware and software. For AI-enabled IoT systems handling sensitive real-time data, data security becomes a key consideration, especially in aerospace and defense applications.

Identifying emerging research trends and future directions in AI and ML applications in mechanical engineering is essential to maintain a leading edge in innovation and address current challenges. Autonomous systems and robotics are also rapidly advancing, with research focusing on AI-driven systems capable of real-time adaptation and decision-making. These developments promote safe and efficient human–machine collaboration in industries such as construction and manufacturing [2, 12].

Recently, Large Language Models (LLMs) have opened new opportunities in mechanical engineering. LLMs are applied in complex data analysis, knowledge management, and human–

machine interaction, including technical document analysis, information synthesis, and design recommendation, thereby facilitating research and development (R&D) processes. They also support anomaly detection, production forecasting, maintenance scheduling optimization, operational cost reduction, and product quality improvement. Furthermore, LLMs can automatically generate code and documentation in computer-aided engineering (CAE) and simulation, accelerating model development, data processing, and system design. With continuous advancements, LLMs are expected to play a key role in real-time monitoring, decision-making, smart manufacturing, and design optimization.

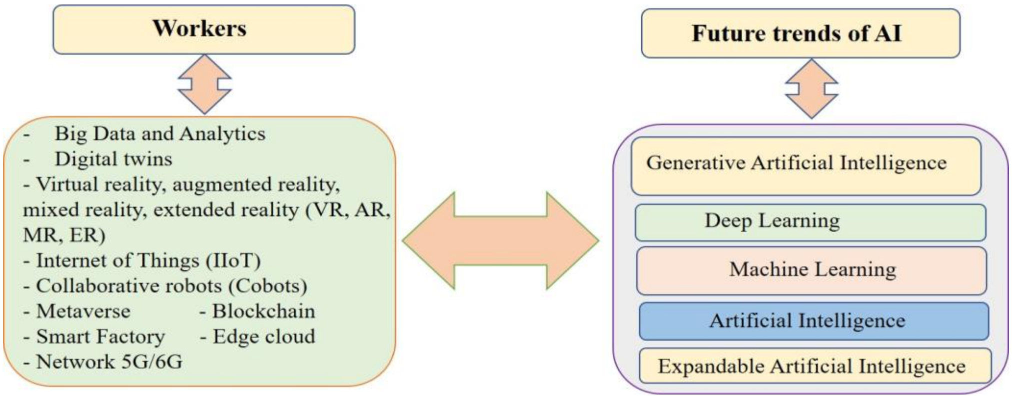

Figure 8. *Future trends of AI.*

Figure 8 illustrates future AI trends impacting mechanical engineering, including generative AI, deep learning, and advanced technologies such as blockchain, AR/VR, and other digital innovations, which collectively enhance human–machine collaboration. These technologies highlight the expanding role of AI in supporting workers, fostering innovation, and improving efficiency in production, design, and system management. Interdisciplinary collaboration, particularly between mechanical engineering and computer science, enables the development of customized AI/ML algorithms for mechanical applications, while optimizing parallel processing and accelerating simulations. Integrating knowledge from fields such as biomechanics and materials science supports the development of models for personalized healthcare, performance prediction, material design, and property characterization. Academia–industry partnerships facilitate the translation of research outcomes into practical solutions, while interdisciplinary research centers and international collaborations enhance knowledge exchange and accelerate AI/ML advancements in mechanical engineering.

7. CONCLUSIONS

The integration of artificial intelligence and machine learning represents a paradigm shift in mechanical engineering, offering unprecedented capabilities for optimizing renewable energy systems, enhancing structural health monitoring (SHM), and improving manufacturing processes. This review highlights how AI and ML techniques have advanced damage detection, predictive maintenance, and real-time monitoring, contributing to more resilient and durable infrastructures. Practical applications are increasingly evident across industries: AI-driven predictive maintenance allows real-time monitoring of machinery, reducing downtime and extending equipment lifespan, while computer vision-based quality control surpasses traditional inspection methods in accuracy, speed, and defect detection. Despite these promising developments, widespread implementation faces challenges such as a shortage of skilled professionals, integration difficulties with legacy systems, data quality limitations, and high deployment costs. Future prospects are promising, driven by hybrid approaches that combine data-driven and physics-based models, innovations in autonomous systems and robotics, and the continued refinement of AI enabled optimization for sustainable design and manufacturing. Collectively, these trends indicate that AI and ML will play a central role in shaping the next generation of mechanical engineering solutions.

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TÓM TẮT

Vai trò của trí tuệ nhân tạo và học máy trong kỹ thuật cơ khí - Tổng quan

Bài báo này trình bày tổng quan về vai trò của trí tuệ nhân tạo (AI) và học máy (ML) trong việc thúc đẩy kỹ thuật cơ khí, nhấn mạnh vào các ứng dụng cụ thể trong từng lĩnh vực đã thúc đẩy tiến bộ công nghệ gần đây. Các ứng dụng như bảo trì dự đoán, đánh giá tính toàn vẹn kết cấu, tối ưu hóa thiết kế thông minh, kiểm tra chất lượng tự động và nâng cao hệ thống năng lượng tái tạo chứng minh khả năng của các phương pháp AI – bao gồm mạng nơ-ron sâu và học tăng cường – trong việc cải thiện hiệu quả hoạt động, giảm thiểu chi phí vận hành và thúc đẩy các giải pháp kỹ thuật bền vững. Bên cạnh các ứng dụng riêng lẻ, bài tổng quan thảo luận về các thuộc tính cơ bản của AI, bao gồm khả năng thích ứng của mô hình, khả năng giải thích và sự kết hợp giữa các kỹ thuật dựa trên dữ liệu với các khung lý thuyết dựa trên vật lý, cho phép áp dụng rộng rãi trên các lĩnh vực kỹ thuật cơ khí. Mặc dù có những tiến bộ này, vẫn còn những vấn đề chưa được giải quyết, đặc biệt là về độ tin cậy của mô hình, chi phí tính toán và tính sẵn có của dữ liệu chất lượng cao. Bằng cách tổng hợp các kết quả nghiên cứu gần đây, nêu bật những hạn chế hiện có và đề xuất các hướng nghiên cứu tiềm năng, bài tổng quan này nhằm cung cấp những hiểu biết có giá trị cho cả các nhà nghiên cứu học thuật và các chuyên gia trong ngành kỹ thuật cơ khí.

Từ khoá: Trí tuệ nhân tạo; Học máy; Công nghiệp 4.0; Kỹ thuật cơ khí.