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Artificial Intelligence in Advance Manufacturing

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ABSTRACT

This paper delves into the evolution of manufacturing systems, strongly influenced by changes in products, technology, business strategies, and production paradigms. It rigorously examines the adoption of human-centric decision-making in collaboration with intelligent systems, along with implications and preparedness for the transition to more responsive, intelligent adaptive systems. This presents a vision for the new Adaptive Cognitive Manufacturing System (ACMS), Artificial intelligence paradigm and provides assertive perspectives for future research, education, and work to drive the evolution of manufacturing systems..

Keywords – Artificial Intelligence, Deep Learning, Machine Learning, Mechanical Testing

INTRODUCTION

[1]The manufacturing sector is on the brink of a significant transformation, propelled by the growing use of sensors and the Internet of Things (IoT), the abundance of data, and breakthroughs in robotics and automation. This shift is leading to widespread digital transformation in factories, forcing manufacturing companies to rethink, review, and reassess their current operations and future strategies in the era known as Smart Manufacturing and Industry 4.0. These advancements, which paint a picture of the future of manufacturing, underscore the central focus of this paper, which is to explore how artificial intelligence (AI) can be instrumental in seizing these opportunities to revolutionize the manufacturing sector in a meaningful way. The adoption of AI in contemporary manufacturing has evolved over time, building on the development of various techniques, including machine learning (ML). Recent progress in computational technology and sensing devices for gathering essential data from processes and machines has made the application of these AI methods practical, sparking interest in their capabilities and advantages. Additionally, examining the latest AI applications reveals specific challenges in manufacturing where AI can offer solutions, thereby enhancing productivity, quality, flexibility, safety, and cost-effectiveness. This knowledge and insight are crucial for the effective application of AI in today's complex industrial settings, each with its unique needs and contexts.The term "Artificial Intelligence (AI)" defines computers' capability to carry out tasks associated with human intelligence. The concept has its origins in the 1950s with the development of the perceptron, a neural network (NN) model. Despite initial challenges, AI research saw a revival with the advent of Machine Learning (ML), particularly deep learning (DL). These methods rely on generalization, inferring overall characteristics by observing individual examples. The focus of AI has shifted to providing support for analytics as tools for human experts in factories. [1]

[2] Artificial Intelligence (AI) stands as a leading technology in Industry 4.0. The accumulation of vast amounts of data through Internet-of-Things (IoT) technology has propelled the development of advanced techniques for retrieving and analyzing information, including AI. This progress is set to revolutionize many sectors of the manufacturing industry, leading to the establishment of smart factories. "Industrial AI" specifically targets AI applications for the manufacturing sector, focusing on crucial aspects such as pattern recognition, analysis of unstructured data, resilience to repetitive tasks, rapid processing speed, and high explainability. Deep learning, a subset of machine learning, is increasingly replacing conventional data analysis methods. Despite challenges related to interpretability and generalization, the potential of deep learning is extensive. However, its direct implementation in manufacturing environments faces resistance due to integration issues and unresolved concerns. This comprehensive review aims to heighten awareness of AI applications across various industrial sectors.[2][3]The transition from theoretical concepts in computer science to practical applications of AI and ML is pivotal for the Industry 4.0 revolution. Governments and industries worldwide unequivocally recognize the strategic importance of these technologies and are actively integrating them into manufacturing operations. This integration presents significant opportunities to enhance efficiency, productivity, and sustainability. However, it also entails substantial challenges, including the cost of infrastructure, the need to recruit staff with expertise, and the potential for security and environmental risks.AI is a broad field in computer science that covers a wide range of techniques and approaches. Most AI programs are designed to solve a specific task, so it would be more accurate to refer to them as artificial narrow intelligence (ANI) rather than AI. In the past, AI programs were mainly expert systems that imitated human decision-making in a

particular task by using hard-coded rules. Later, heuristic-based approaches like evolutionary algorithms emerged, which can independently discover solutions while optimizing a performance metric. In recent years, AI systems based on machine learning (ML), especially deep learning, have become popular. These AI/ML systems can consist of various different techniques and are not necessarily monolithic.[3]

MATERIAL & METHODES

The use of AI and ML techniques has completely revolutionized composite design through additive manufacturing (AM) methods like AI-guided 3D printing and 4D printing. This approach significantly accelerates simulations, optimizes material selection, and drastically reduces time and costs. AI/ML techniques unequivocally offer powerful tools for advancing the designs of high-performance composites and innovative functional materials.

[4]The transition from linear to circular economic models is imperative to tackle the global climate crisis head-on. Current linear "take-make-waste" production and consumption patterns heavily rely on fossil fuels, resulting in substantial greenhouse gas emissions and resource depletion. While transitioning to renewable energy and improving energy efficiencies are crucial, they only address about 55% of the emissions. Transitioning to circular, decentralized supply chains with locally sourced materials and accessible manufacturing tools can significantly reduce transportation costs and carbon footprints. Decentralized manufacturing enables on-demand production, minimizes waste, and brings production closer to consumption. However, the variability in locally sourced recycled and renewable materials currently poses a challenge to the manufacturing process. For example, wood feedstocks of the same species can exhibit significant differences in mechanical properties based on varying conditions. Democratizing mechanical testing is crucial in overcoming challenges in sustainable materials sourcing. By providing local access to testing and utilizing advanced modeling, we can design products adaptable to varying feedstock properties. Post-manufacturing testing is essential to ensure product quality and reliability. This approach strongly aligns with United Nations Sustainable Development Goals.[4].[5]This special issue presents groundbreaking research on harnessing modern AI methods to significantly enhance engineering design. AI plays a crucial role in automating knowledge extraction, aiding early design ideation, and solving previously unsolved engineering problems. It empowers engineers to overcome cognitive limits and expand design spaces. AI methods also drive efficient design revision and fundamentally reshape our approach to design. Integrating complementary directions is imperative for a comprehensive understanding of how AI methods can propel advancements in engineering design for the benefit of society.[5]

RESULTS

[6]The proposed paper presents a feature learning framework that seamlessly integrates engineering knowledge with deep learning for additive manufacturing (AM) quality monitoring. It effectively overcomes the limitations of deep learning in assimilating engineering knowledge and interpreting process–quality relationships. The framework introduces a 3D neighborhood model to capture spatiotemporal variations in melt pools and a robust regression model for predicting internal density variations. Secondary research results unequivocally demonstrate the framework's superiority over traditional methods and black-box learning in providing quality-related features and accurately predicting internal density variations.[6][7]In the advancing knowledge economy, the intuition economy and the allocation economy will harness technology and data analytics to amplify human creativity and optimize resource allocation.. This research delves deep into the transformative impact of rapid technological advancements, particularly in artificial intelligence and automation, on the future of work and the economy. It definitively predicts that by 2030, approximately half of all global working tasks may be automated, affecting nearly 800 million jobs. As routine manual and cognitive jobs decline, there will be an undeniable surge in the demand for creative, social, and emotional skills. This shift from knowledge-based to intuition-based work unequivocally allows humans to focus on creativity, innovation, and emotional intelligence while AI takes over data processing and mechanistic tasks. However, this transition demands unequivocal implementation of robust reskilling policies, dynamic education systems, and supportive labor market transitions. Additionally, the advancements in computing power and IoT unquestionably enable superior optimization of resource allocation, forming the "allocation economy."

While these developments offer unprecedented opportunities for human creativity and innovation, they undeniably pose challenges related to data ethics, bias, and inclusion. It is absolutely crucial to establish unequivocal guardrails for data ethics and create unwaveringly supportive policy environments to balance efficiency with social goods. Overall, successfully navigating these changes will unequivocally define the contours of inclusive growth, necessitating unwavering collaboration among academia, government, and industry to develop supportive policies, future-ready education, and ethical technology[7].[8]The paper introduces an ensemble model utilizing transfer learning and Vision Transformer (ViT) to effectively detect product abnormalities. The model, integrated with a cyber-physical system, efficiently addresses challenges in identifying small defects during manual processing and manages the high product volume for quality control. The learning process incorporates noise removal, feature extraction, and classification, all seamlessly executed by the ensemble model ETLViT. Figure 3 clearly outlines the architecture of ETLViT.[8]

CONCLUSIONS

In conclusion, this paper underscores the critical importance of implementing cyber-physical systems (CPS) in production industries to significantly enhance and automate quality assurance processes. The proposed ETLViT methodology, integrating CPS with an ensemble model for defect detection, demonstrates superior performance when compared to alternative approaches. This emphasizes the pivotal role of Vision Transformers in improving accuracy and reliability of predictions. Future research should prioritize optimizing the ensemble model and exploring diverse CPS integration configurations tailored for real industrial environments.

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