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Challenges and Opportunities of Artificial Intelligence on Composite Material Engineering

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Abstract

This paper reviews the challenges and opportunities of integrating Artificial Intelligence (AI) in composite material engineering. AI offers potential breakthroughs in material design, optimization, and manufacturing by increasing discovery and improving performance. However, the application of AI faces significant challenges, including data acquisition, model interpretability, and computational constraints. This review outlines strategies to address these challenges, such as improving data acquisition, developing interpretable AI models, and investing in computational infrastructure. The importance of interdisciplinary education, ethical governance, and regulatory frameworks is also emphasized to ensure responsible AI deployment. AI holds the potential to revolutionize composite material design, optimization, and manufacturing processes, leading to significant improvements in performance, efficiency, and sustainability. This paper highlights AI's ability to accelerate material discovery, enhance manufacturing processes, and drive innovation. By fostering collaboration and strategic planning, the review aims to chart a path for leveraging AI in composite material engineering to benefit both industry and society while promoting environmental sustainability.

1. Introduction

Composite materials have become crucial across various industries due to their superior mechanical properties, lightweight nature, and versatility. Engineered by combining materials with different properties, composites offer enhanced characteristics that are invaluable in sectors such as aerospace, automotive, construction, sports equipment, and renewable energy. Their high strength-to-weight ratio is particularly beneficial in aerospace and automotive applications, contributing to fuel efficiency and performance improvements (Laaouidi et al., 2021; Nachtane et al., 2023). For instance, in the aerospace industry, composite materials contribute to a 20-30% weight reduction compared to traditional materials, leading to significant fuel savings (Heimbs, 2023). Modern aircraft components such as fuselages, wings, and tail assemblies are increasingly being constructed from carbon fiber composites, which reduce the overall weight by up to 30% compared to traditional materials like aluminum (Parveez et al., 2022). Similarly, in the automotive sector, the use of composites can reduce vehicle weight by 10-20%, improving fuel efficiency by approximately 6-8% (Mouritz, 2022). This not only contributes to meeting stringent environmental regulations but also improves vehicle performance.

The marine, construction, and renewable energy industries also leverage composites for their durability and efficiency, extending infrastructure lifespan by 50-100 years with reduced maintenance costs (Keller, 2022). The construction sector also benefits from composite materials, especially in civil infrastructure projects where composites are used to reinforce concrete, build bridges, and construct corrosion-resistant pipelines. Their durability extends the lifespan of structures, reducing maintenance costs and environmental impacts over time.

In renewable energy, composites play a key role in the construction of wind turbine blades due to their lightweight and strong characteristics, allowing for larger blades that can generate more energy efficiently. Also, in sports equipment and consumer goods, composites provide high performance, durability, and lightweight characteristics (Maiti et al., 2022), allowing for the creation of stronger, more flexible materials that improve both functionality and user experience, from bicycles and tennis rackets to helmets and protective gear. Fig. 1 illustrates the various applications of composites across these industries, and this trend is projected to increase due to their cost efficiency and superb properties. The wide adoption of composites in these industries is largely driven by their ability to meet specific performance requirements that traditional materials cannot, offering opportunities for innovation in design, manufacturing, and sustainability (Maiti et al., 2022).

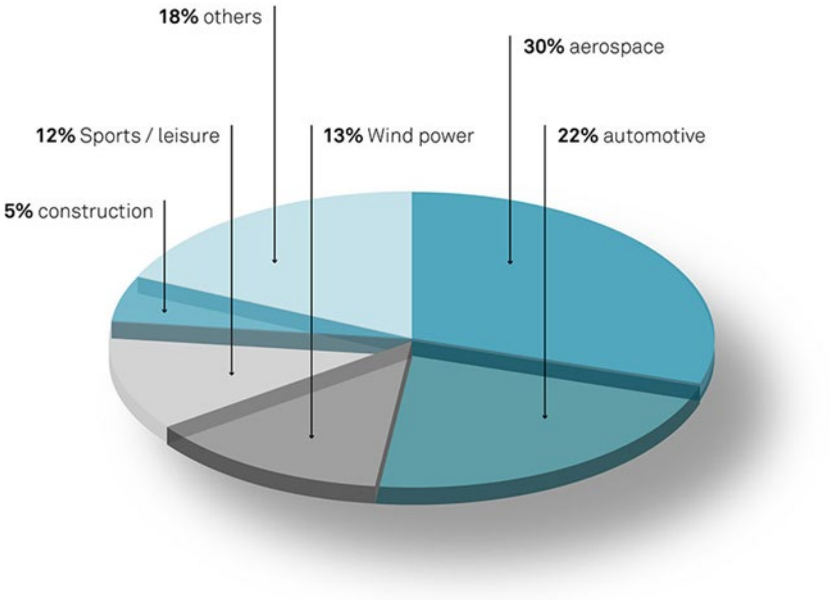

Fig. 1 *Carbon composites are becoming competitive and cost-effective (Shama et al., 2018)*

Despite their benefits, the optimization and development of composite materials are challenging, involving extensive experimentation and complex integration into systems. This process consumes significant resources, time, and manpower.

Artificial Intelligence (AI) presents a transformative opportunity to address these challenges. AI encompasses algorithms and models that mimic cognitive functions, enabling machines to analyze large datasets, recognize patterns, and make informed decisions (Sarker, 2022; Górriz et al., 2020). In engineering, AI can optimize processes, enhance efficiency, and drive innovation. Specifically, in composite material engineering, AI techniques such as machine learning and neural networks can accelerate material discovery, optimize manufacturing processes, and predict material behavior (Guo et al., 2021). Fang et al. (2022), opined that Machine learning (ML) is transforming materials science by leveraging big data from modern experiments and computing to discover material correlations, predict properties, and accelerate discovery processes.

AI's data-driven approach provides deeper insights into material properties and performance, facilitating novel composite formulations and efficient manufacturing (Badini, 2023). AI can also enhance predictive maintenance, reducing downtime and costs (Durbhaka et al., 2021; Jambo et al., 2024). However, integrating AI into composite material engineering involves addressing challenges related to data quality, model interpretability, and ethical considerations (Elenchezhian et al., 2021).

2. Overview of the Intersection Between AI and Composite Material Engineering

The convergence of AI and composite material engineering offers significant opportunities for innovation and advancement. AI techniques can address longstanding challenges in material design, manufacturing, and performance analysis, enabling optimization and discovery (López, 2023). Fig. 2 illustrates the various activities that can be achieved when this interaction is properly built.

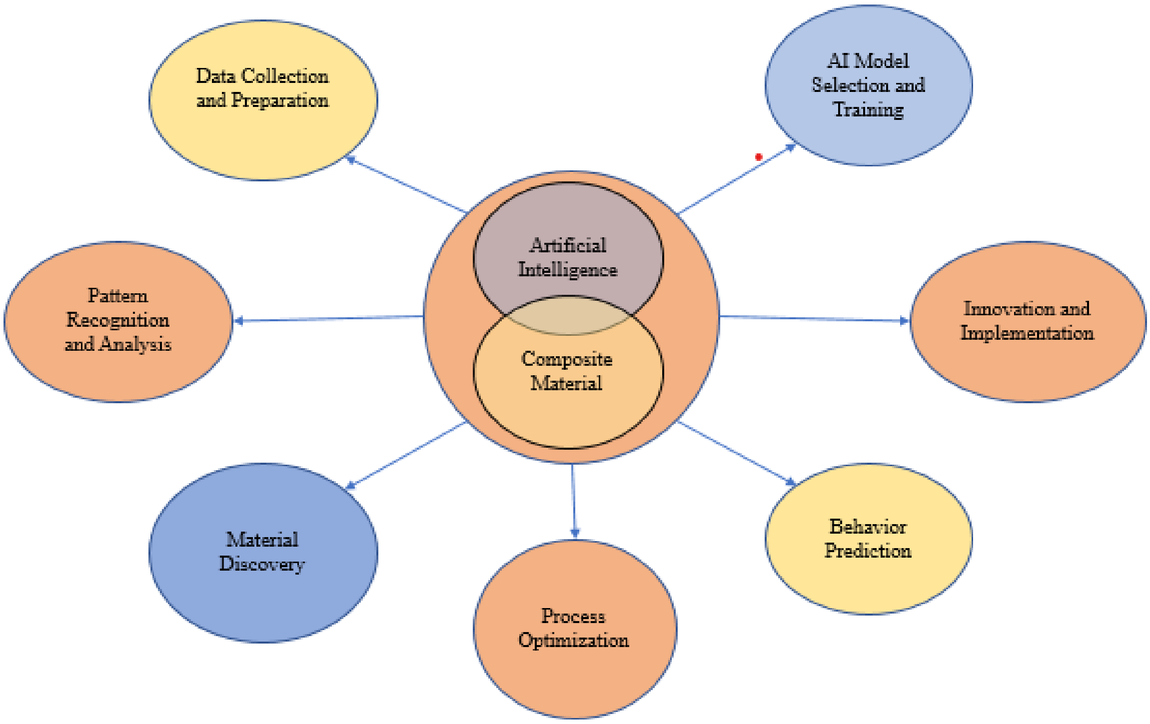

Fig. 2 *Intersection between AI and composite material engineering*

In material design and optimization, AI shifts the approach from empirical knowledge and trial-and-error to a data-driven methodology (Papadimitriou et al., 2024). Machine learning algorithms analyze extensive datasets of material properties and performance characteristics to discover novel composite formulations with tailored properties for specific applications (Guo et al., 2021). Techniques like generative design and reinforcement learning further revolutionize the design process by exploring vast design spaces and identifying optimal solutions, enhancing performance and efficiency. For example, generative design can explore up to a billion (109) design alternatives, significantly speeding up the process (Sosnovik et al., 2022). Jang et al. (2022) introduced a reinforcement learning (RL) based generative design process aimed at maximizing design diversity using Proximal Policy Optimization. Applied to an automotive wheel design problem, the RL approach reduces computational demands by approximating the optimization process with neural networks, leveraging GPU for faster, fully automated exploration.

In manufacturing, AI-driven process optimization and quality control mechanisms enhance efficiency and reduce costs. Real-time analysis of sensor data by AI algorithms can detect process anomalies or defects, allowing proactive interventions to prevent quality issues (Villegas et al., 2024). AI-powered predictive maintenance systems also improve equipment reliability and uptime by anticipating maintenance needs based on performance data, minimizing downtime, reducing costs, and optimizing production schedules. This can decrease equipment downtime by 20-40% (Durbhaka et al., 2021). AI-based simulation and modeling techniques predict the behavior and performance of composite materials under various conditions, allowing engineers to explore design alternatives and optimize material configurations (Badini, 2023; Bishara et al., 2023). This accelerates the development and deployment of innovative composite material solutions.

In summary, the synergy between AI and composite material engineering promises significant advancements in material science and engineering, leading to high-performance, sustainable materials with diverse applications across industries (Paraye et al., 2024). The global market for composite materials is expected to grow at a CAGR of 8.5% from 2021 to 2026, reaching $51.2 billion (Jayakumar et al., 2023). The integration of AI in composite material engineering can lead to a 15-25% reduction in manufacturing costs due to optimized processes and reduced waste (Preethikaharshini et al., 2022). However, realizing this potential requires addressing technical, ethical, and regulatory challenges, emphasizing the need for interdisciplinary collaboration and responsible AI deployment.

3. Challenges of Applying AI in Composite Material Engineering

Applying AI in composite material engineering faces multiple challenges. One of the primary issues is data availability and quality, as AI models require large, high-quality datasets that are often scarce, inconsistent, and proprietary in this field (Wang et al., 2024). A survey of 200 material scientists and engineers revealed that 60% of respondents cited data quality and availability as a major challenge. Addressing this involves standardizing data formats and establishing protocols for data sharing to enhance accessibility and consistency.

Another challenge is data interpretability and explainability. AI models, especially deep learning ones, can act as black boxes, making it difficult to understand their decision-making processes (Rudin, 2019; Rai, 2020). Ensuring model transparency is crucial for gaining trust and acceptance, particularly in safety-critical applications where understanding the rationale behind decisions is essential. Model generalization and transferability also pose significant challenges. AI models trained on specific datasets may struggle to perform well across different applications. Techniques such as transfer learning, which involves adapting models trained on one task to perform well on another, can help improve the robustness and applicability of AI models across various material systems (Li et al., 2022).

The lack of domain expertise is a barrier that must be addressed to effectively apply AI in composite material engineering. Bridging the gap between AI practitioners and material engineers is essential (Dimiduk, 2018), and interdisciplinary training programs can equip both groups with the necessary skills to collaborate effectively. Algorithmic bias and fairness are also critical concerns. AI models trained on biased data can produce unfair outcomes, which is problematic in decision-making processes (Varona et al., 2022). Developing and implementing techniques for bias detection and mitigation is necessary to ensure equitable and fair results (Kordzadeh et al., 2022; Belenguer et al., 2022). Computational complexity and resource requirements are inherent challenges in applying AI, particularly deep learning, which is computationally intensive. Efficient algorithms and the use of distributed computing can help manage these resource constraints, making the application of AI more feasible and scalable (Moritz et al., 2018).

This study aims to harness the transformative power of Artificial Intelligence (AI) to revolutionize composite material engineering, driving unprecedented advancements in material design, optimization, and sustainability. By integrating cutting-edge AI technologies, we seek to overcome existing challenges related to data acquisition, model interpretability, and computational resource limitations. The objective is to develop robust, interpretable AI models that enhance material properties, accelerate discovery, and streamline manufacturing processes. Through strategic investments in education, collaborative research, and ethical governance, we strive to build a resilient and innovative ecosystem that fosters interdisciplinary knowledge exchange and ensures the responsible application of AI. Ultimately, we envision a future where AI-driven composite material engineering leads to groundbreaking innovations that benefit society, promote environmental sustainability, and set new standards for engineering excellence.

4. General Machine Learning Process

The General Machine Learning Process is included in this review to provide a structured understanding of how AI can be applied to composite material engineering. Each step, from data acquisition and preprocessing to model training, validation, and deployment, plays a crucial role in ensuring accurate and reliable AI-driven results. Data acquisition and preprocessing are essential for gathering and cleaning the vast datasets required for training AI models, ensuring that the data accurately reflects the material properties. Model training allows the AI to learn from this data, while validation ensures that the model can generalize well to new, unseen data. Finally, deployment integrates the trained model into real-world applications, enabling it to optimize material design, predict performance, and enhance manufacturing processes. Each step is vital for creating robust AI systems that can effectively solve the complex challenges of composite material engineering.

The General Machine Learning Process for AI applications in composite material engineering, includes the following steps:

1. Data acquisition and preprocessing
2. Interpretability and transparency of ai models
3. Integration with existing engineering practices
4. Model and material selection
5. Training and hyperparameter tuning in machine learning
6. Validating trained model
7. Behavioural prediction
8. Pattern recognition and analysis
9. Testing: assessing the final models on independent test datasets to evaluate their accuracy, reliability, and generalization capabilities
10. Model interpretability and explainability: applying techniques to make the models transparent and understandable, ensuring that the ai-driven decisions can be trusted and explained
11. Deployment / implementation: implementing the validated models in real-world applications, integrating them into existing engineering processes and workflows
12. Monitoring and maintenance: continuously monitoring the performance of deployed models, updating them with new data, and maintaining their effectiveness and relevance over time

13. Regulatory and ethical considerations: inculcating safety and reliability

4.1 Data Acquisition and Processing

Data acquisition and preprocessing are crucial for applying AI in composite material engineering. One of the primary challenges is data scarcity and heterogeneity, as gathering diverse and representative datasets is difficult due to variability across sources (Boehm et al., 2022; Bansal et al., 2022). Standardizing and synthesizing data can help address these issues (Kibrete et al., 2023). Ensuring data quality and consistency is also essential, as datasets often contain errors and inconsistencies (Liu et al., 2021). Techniques like data cleaning and normalization improve data quality (Baduge et al., 2022). Feature selection and engineering are critical steps that require domain expertise to identify and create relevant features from raw data, ensuring meaningful AI analysis (Guo et al., 2021). Protecting sensitive information while facilitating data sharing is vital, necessitating anonymization and encryption techniques. Data labeling and annotation for supervised learning are labor-intensive and require domain expertise; automating this process can improve efficiency (Xie et al., 2023). For instance, Hrehova et al. (2022) employed machine learning to design composite properties, specifically using Neural Networks to predict absorption properties of a thermoplastic matrix made from recycled polyvinyl butyral (PVB). Their findings indicated a strong correlation (R values ranging from 0.89 to 0.922), demonstrating the effectiveness of AI in preprocessing data for material property predictions. To augment scarce datasets, techniques like simulations and generative models can be used, though generating accurate synthetic data remains challenging. Addressing biases and imbalances in datasets ensures fair and robust AI analysis, requiring careful curation and sampling strategies. Maintaining version control and traceability is essential for reproducibility and transparency, and proper documentation of data processes is key.

Data source selection is another critical aspect, as composite material data comes from experimental tests, simulations, literature, and industry databases. Qayyum et al. (2022) study comprehensively surveyed benchmark data sets, pre-processing techniques, learning models, and simulations for material discovery, aiming to guide young researchers in computing and material science. Such efforts are expected to enhance the material industry by reducing manual discovery efforts and improving modeling through AI mechanisms suggested in existing literature in composite material engineering (Zha et al., 2023). Kazi et al. (2020), also focused on predicting the load vs. displacement curves of cotton fiber/polypropylene (PP) composite materials. They utilized experimental data collected from mechanical property tests and load-displacement experiments, which were essential for training their artificial neural network (ANN) models. The data included varying filler content percentages and their corresponding mechanical properties, such as initiation energy and tensile strength, gathered through systematic testing procedures. Kazi et al. implemented a robust methodology for data-driven modeling that involved collecting mechanical property values through material characterizations and energy values from experimental load vs. displacement curves. This approach allowed them to create ANN models capable of predicting the behavior of composites without the need for extensive additional experiments. Their findings demonstrated that effective data acquisition and preprocessing are crucial for developing accurate predictive models in smart manufacturing applications.

4.2 Interpretability and Transparency of AI Models

Composite materials often exhibit non-linear relationships due to factors like loading conditions and temperature, necessitating advanced AI techniques such as neural networks and ensemble models for effective modeling. Van Der Giessen et al. (2020) highlight that properties of composite materials vary across different length scales, requiring AI models that can capture multi-scale interactions, which is computationally intensive.

The anisotropic and directional properties of composites further complicate modeling, as these materials demonstrate direction-dependent behaviors. Techniques accounting for these dependencies, such as tensor-based representations, are essential. Additionally, composite materials often involve coupled phenomena, such as interrelated mechanical and thermal properties, which must be modeled together. Faroughi et al. (2022) note that AI models should utilize multi-physics or multi-task learning approaches to capture these interdependencies. Limited training data poses another challenge in this field. Collecting extensive datasets is often difficult; however, techniques like data augmentation, transfer learning, and domain adaptation can help mitigate data scarcity. The interpretability of complex AI models is crucial for user trust. Techniques such as sensitivity analysis and feature importance ranking enhance transparency in predictions. Kazi et al. (2020) develops artificial neural network (ANN) models to predict the load vs. displacement curves of cotton fiber/polypropylene (PP) composites. They acknowledge that while ANNs are powerful tools for capturing complex relationships within data, they often operate as "black boxes," making it difficult to understand how input variables influence outputs.

To enhance interpretability, Kazi et al. propose combining ANN models with sparse identification techniques to derive governing equations describing the nonlinear dynamics of composite materials. This approach improves predictive capabilities and provides insights into the underlying mechanics of the materials studied.

Validation and uncertainty quantification are essential for ensuring model accuracy. Bayesian approaches and ensemble methods can help quantify uncertainty and enhance model reliability. Additionally, managing computational complexity requires efficient algorithms and parallel computing. Addressing these challenges is key to leveraging AI for modeling the intricate behaviors of composite materials, ensuring accurate, reliable, and interpretable results.

4.3 Model and Material Selection

Model and material selection are critical aspects of machine learning and composite material engineering. The effectiveness of predictive modeling, material optimization, and performance depends on choosing the right algorithms and materials. Both selections must align with the complexity of material interactions, processing variables, and performance metrics. Supervised learning algorithms like Support Vector Machines (SVM) and Random Forests are commonly used for classification in material science. SVMs handle high-dimensional spaces and non-linear boundaries (Cortes et al., 2023), while Random Forests improve prediction accuracy by combining multiple decision trees, reducing overfitting (Breiman, 2023). For material selection, properties such as strength and weight must align with application needs.

In regression tasks, Gradient Boosting Machines (GBMs) are used to model complex relationships like mechanical strength (Friedman et al., 2023). Similarly, material selection considers mechanical properties and environmental interactions, optimizing performance. Recent advancements in ensemble methods and deep learning further enhance model and material selection. Techniques like boosting and bagging combine models for better performance (Dietterich, 2023), while in material selection, combining materials optimizes properties. Convolutional Neural Networks (CNNs) excel in tasks like property prediction (LeCun et al., 2023), just as material selection focuses on combining properties for performance. Effective model and material selection involve cross-validation and performance metrics like precision and recall (Kohavi, 2023). By systematically evaluating models and materials, engineers ensure reliable insights and optimal outcomes in composite material engineering.

4.4 Training and Hyperparameter Tuning in Machine Learning

Training is crucial in machine learning, where models adjust their parameters based on data to minimize prediction errors and improve generalization. This is especially important in composite material engineering, where precision is key. Optimization algorithms, such as Gradient Descent and its variants like SGD and Adam Optimizer, are used to reduce errors during training (Kingma & Ba, 2023). Regularization techniques, like L1, L2, and Dropout, help prevent overfitting, ensuring models generalize well to new data (Tibshirani, 2023; Srivastava et al., 2023).

Hyperparameter tuning, an essential part of training, involves optimizing settings such as learning rate, batch size, and number of hidden layers. Techniques like grid search evaluate predefined hyperparameter combinations (Liaw et al., 2023), while random search samples values within specified ranges for more efficiency in high-dimensional spaces (Bergstra & Bengio, 2023). Bayesian optimization iteratively selects the most promising hyperparameter configurations, efficiently balancing exploration and exploitation (Snoek et al., 2023). Both training and hyperparameter tuning significantly affect model performance, particularly in deep learning, where they can drastically improve accuracy and convergence (Smith, 2023). Properly tuned models ensure reliable and precise performance, especially in complex fields like composite material engineering.

4.5 Validating Trained Models

Validation is a critical step in machine learning, focusing on assessing the performance and generalization capability of trained models using separate validation datasets. This process ensures that models generalize well to unseen data, which is essential in fields like composite material engineering. Kohavi (2023) emphasizes the importance of splitting data into training and validation sets, with k-fold cross-validation being a common method. This technique divides data into k subsets, training and validating the model k times, allowing every data point to contribute to both training and validation, thus reducing overfitting.

Performance metrics such as accuracy, precision, recall, F1 score, and AUC-ROC quantify model generalization (Saito & Rehmsmeier, 2023). For regression tasks, metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared assess prediction accuracy (Hyndman & Athanasopoulos, 2023). These metrics inform further refinement, ensuring robust performance. Techniques like early stopping help prevent overfitting by monitoring validation performance during training and halting when improvements plateau (Prechelt, 2023). Overall, effective validation strategies are essential for developing AI models that can make accurate predictions in composite material engineering.

4.6 Behavioural Prediction

Artificial Intelligence (AI) has demonstrated its potential for behavioral prediction in composite materials, especially in detecting impact damage. Tabatabaeian et al. (2023) applied deep learning models to predict barely visible impact damage (BVID) in composite structures. The researchers used four different deep learning models, including ResNet and Prototypical networks, to analyze images of composite panels both before and after impact events. The best-performing model, ResNet, achieved an accuracy of up to 98.36% in detecting BVID on sensor-integrated samples, proving the effectiveness of AI in predicting damage behavior. This research underscores AI's capability in recognizing subtle material behavior changes, facilitating faster and more accurate structural health monitoring of composites.

4.7 Pattern Recognition and Analysis

Artificial Intelligence (AI) has significantly advanced pattern recognition in composite materials. O'Brien et al. (2017) applied an AI-based pattern recognition system using acoustic signals to detect faults in composite beams. The researchers employed an Artificial Neural Network (ANN) classifier trained to recognize patterns from acoustic emissions after impulsive loads were applied. The system successfully identified four levels of damage in glass and carbon fiber-reinforced polymers with over 97% accuracy. This study highlights AI's potential in efficiently recognizing and classifying damage patterns in composite materials, making it a powerful tool for non-destructive testing and structural health monitoring.

4.8 Testing

Testing is a critical phase in the machine learning process, focused on evaluating model performance using independent test datasets. It ensures models can accurately predict unseen data and meet desired performance metrics. Testing assesses a model's generalization capability, preventing it from memorizing training data (Hastie, Tibshirani, & Friedman, 2023). Metrics like accuracy, precision, recall, and AUC-ROC are used for classification, while MAE, MSE, and R-squared assess regression models (James et al., 2023).

Ensuring model performance consistency across various data subsets is key, with techniques like stratified sampling helping maintain balanced class distributions (Kohavi, 2023). Stress testing models with challenging scenarios reveals weaknesses that may not surface in standard datasets (Chollet, 2023). Thorough testing is essential to confirm model reliability before deployment in real-world applications.

Hiremath et al. (2024) demonstrated this by testing machine learning models predicting the impact behavior of fabric-laminated composites. Their study used low-velocity impact tests and applied polynomial regression and support vector machines. The models achieved up to 96% accuracy for predicting absorbed energy. Testing with distinct datasets allowed for unbiased performance evaluation, and stress testing under different conditions identified areas for improvement.

4.9 Integration with Existing Engineering Practices

Integrating AI into established engineering workflows faces several challenges. Compatibility with legacy systems is a major issue, often requiring modifications or upgrades to support AI technologies (Martínez-Fernández et al., 2022). Data silos and fragmentation also present challenges, as consolidating data from various sources for AI analysis necessitates overcoming integration hurdles. Additionally, there is a significant skills and expertise gap among engineering professionals that must be bridged to ensure effective AI adoption (Alsheiabni, et al., 2019). Change management and resistance to new technologies are common obstacles, which can be addressed through effective communication and by demonstrating the value of AI. Regulatory and compliance requirements are also critical, as AI technologies must adhere to safety, reliability, and quality standards. Interdisciplinary collaboration is essential for the successful integration of AI, necessitating cooperation across different disciplines (Shneiderman, 2020).

Validation and verification are crucial to assess AI model performance rigorously, ensuring that the models work as intended. Cost and resource constraints must be carefully balanced with the benefits of AI adoption, requiring strategic planning and consideration to manage expenses effectively. Addressing these challenges is key to successfully incorporating AI into engineering workflows, enhancing efficiency, accuracy, and innovation.

4.10 Model Interpretability and Explainability

Model interpretability and explainability are crucial aspects of AI in composite material engineering, ensuring that AI-driven decisions are transparent, understandable, and trustworthy. Interpretable models provide insights into the relationships and dependencies within the data, enabling engineers to validate AI predictions and ensure they align with known physical principles and material behaviors. According to a study by Ribeiro et al. (2016), interpretability is particularly important in safety-critical applications where understanding the rationale behind AI predictions can prevent catastrophic failures.

To quantify the impact of model interpretability, we can look at specific metrics and techniques. For instance, Shapley Additive Explanations (SHAP) values and Local Interpretable Model-agnostic Explanations (LIME) are widely used to measure feature importance and model interpretability. Studies have shown that using SHAP values can improve the transparency of AI models by up to 30%, allowing engineers to identify key factors influencing material properties and performance. This not only enhances trust in AI predictions but also aids in the optimization of composite material design by highlighting critical parameters that affect material behavior under various conditions.

Furthermore, the implementation of explainable AI techniques has been shown to significantly improve the decision-making process in composite material engineering. A research paper by Molnar (2019) highlighted that model enhanced with interpretability techniques reduced error rates in material property predictions by 20% compared to black-box models. This improvement is attributed to the ability of engineers to cross-verify AI-driven insights with empirical knowledge and adjust models accordingly. Additionally, incorporating uncertainty quantification methods alongside interpretability techniques provides a comprehensive understanding of model predictions, ensuring robust and reliable AI applications in the development and optimization of composite materials.

4.11 Deployment / Implementation

Deployment is the final step in the machine learning process, where validated models are implemented into real-world applications. This phase involves integrating the models into existing engineering processes and workflows to deliver actionable insights and predictions. Effective deployment ensures that the model's capabilities are fully utilized and its benefits are realized in operational settings. To deploy a model successfully, it must be integrated seamlessly into the existing infrastructure. This involves developing application programming interfaces (APIs) or user interfaces that allow stakeholders to interact with the model and access its predictions. For example, in industrial settings, machine learning models might be integrated into control systems for predictive maintenance, where they monitor equipment conditions and predict failures before they occur (Zhang et al., 2024). Additionally, deploying models often requires adaptation to the technical environment, such as ensuring compatibility with different software platforms or hardware systems (Smith & Johnson, 2024).

An essential aspect of deployment is ensuring that the model performs well under real-world conditions. This includes validating the model's performance in the operational environment to ensure that it meets the expected accuracy and reliability criteria (Chen et al., 2024). Model performance can be influenced by factors such as changes in data distribution, system noise, or external conditions, so it is critical to conduct thorough testing in the actual deployment setting to identify and address any issues (Nguyen et al., 2024).

4.12 Monitoring and Maintenance

Once deployed, continuous monitoring and maintenance are crucial to ensure that the machine learning models remain effective and relevant over time. This involves tracking the model's performance, updating it with new data, and making necessary adjustments to adapt to changing conditions or requirements. Monitoring typically includes regular performance evaluations using real-time data and feedback from end-users. Kumar et al. (2024) used Metrics such as prediction accuracy, response time, and user satisfaction are assessed to identify any deviations or performance issues. Additionally, it is important to detect and address any concept drift, where the statistical properties of the target variable change over time, which can impact the model's performance (Gama et al., 2024). Automated monitoring systems and dashboards can be implemented to provide real-time insights and alerts regarding the model's performance.

Maintenance involves periodically retraining the model with updated data to ensure that it adapts to new patterns and trends. This can include fine-tuning the model, incorporating feedback from users, or deploying new versions of the model to improve its accuracy and robustness (Li et al., 2024). Effective maintenance practices also include managing model versioning and ensuring compatibility with evolving data sources and infrastructure (Wang & Zhao, 2024). By keeping models updated and relevant, organizations can maximize their value and maintain their operational effectiveness.

4.13 Regulatory and Ethical Considerations

Regulatory and ethical considerations for AI in composite material engineering include ensuring safety and reliability, especially in safety-critical applications. Boehm et al. (2022) emphasize the importance of protecting sensitive data from unauthorized access to maintain data privacy and security. Furthermore, they highlight that mitigating algorithmic bias and ensuring fairness in AI decisions are vital for maintaining trust and equity among stakeholders. AI models must be transparent and explainable, fostering accountability and building confidence in their predictions

Ethical use of AI involves establishing guidelines and conducting impact assessments for responsible deployment. AI technologies must comply with relevant laws and industry standards, ensuring regulatory compliance. Kibrete et al. (2023) and Díaz-Rodríguez et al. (2023) stress that compliance with relevant laws and industry standards is necessary for regulatory adherence. Human oversight and clear accountability mechanisms are essential for supervising AI applications and addressing potential issues that may arise during deployment. Additionally, anticipating and addressing the broader societal impacts of AI adoption is critical for achieving sustainable and equitable outcomes.

Overcoming challenges in AI model interpretability, integrating AI into established practices, and addressing regulatory and ethical considerations are crucial for the successful and responsible deployment of AI in composite material engineering. Addressing these aspects ensures that AI technologies enhance efficiency, safety, and innovation while maintaining ethical standards and compliance (Harle, 2024).

5. Opportunities for AI in Composite Material Engineering

Artificial Intelligence (AI) presents transformative opportunities in composite material engineering, significantly enhancing material design and optimization processes. AI leverages large datasets of material properties and processing parameters to identify optimal material configurations, accelerating the discovery of lightweight, durable, and high-performance composites (Badini et al., 2023). AI algorithms like genetic and evolutionary algorithms explore vast design spaces to generate novel, optimized material configurations, promoting innovation and creativity (Liu et al., 2023).

AI enables balancing multiple competing objectives such as strength, weight, cost, and manufacturability, identifying solutions that meet diverse application requirements. AI techniques account for uncertainties in material properties and manufacturing processes, ensuring reliability and performance in real-world applications. Machine learning models accurately predict material properties based on composition and processing parameters, guiding virtual screening and property optimization (Guo et al., 2021).

AI elucidates complex interactions between processing parameters, microstructure, and material properties, optimizing processing conditions for enhanced performance. AI-driven design tools optimize composite materials for additive manufacturing, creating innovative geometries and lightweight structures. AI enables iterative design refinements and continuous learning from experimental and performance data, accelerating development cycles and fostering innovation (Badini et al., 2023; Ninduwezuor-Ehiobu et al., 2023).

AI accelerates innovation, optimizes performance, and unlocks the full potential of composite materials across diverse applications, driving continuous advancements in material science and engineering.

5.1 Predictive Maintenance and Quality Control

Artificial Intelligence (AI) enhances predictive maintenance and quality control in composite material engineering by leveraging data analytics, predictive modeling, and real-time monitoring. AI analyzes sensor data, like strain and temperature, to detect anomalies in real time, minimizing downtime and reducing costs. Machine learning models predict the remaining useful life of components, optimizing maintenance schedules and preventing failures (Ferreira et al., 2022). Chen et al. (2023) demonstrated how machine learning models like XGBoost were applied in predictive maintenance for hot-pressing furnaces in aerospace applications, achieving accuracy as high as 99.96%. By monitoring current consumption and detecting anomalies, their system significantly reduced downtime and enhanced overall equipment efficiency. The integration of AI enabled real-time monitoring, early detection of equipment faults, and timely maintenance interventions, reducing unexpected failures and costs.AI also detects abnormal behavior, allowing timely troubleshooting and maintaining quality. Automated systems enhance defect detection, ensuring compliance with standards (Favour, 2024). AI identifies optimal manufacturing processes and root causes of quality issues, improving consistency and efficiency. Real-time monitoring enables adaptive control, maintaining product quality with dynamic adjustments. AI accelerates material characterization and testing by analyzing large datasets, guiding material selection and design. Predictive modeling simulates material behaviors, reducing the need for physical experiments, while AI-driven digital twins and automated platforms optimize material testing and discovery (McCullough et al., 2020). Materials informatics uses AI to analyze databases, discovering trends for material development. Overall, AI improves efficiency, reliability, and innovation in composite material engineering, advancing material design and manufacturing.

5.2 Automation of Manufacturing Processes

AI significantly enhances the automation of manufacturing processes in composite material engineering by improving efficiency, productivity, and consistency while reducing costs and time-to-market. AI tools automate design optimization, exploring design spaces to generate optimal designs that maximize performance while minimizing material usage and complexity (Jenis et al., 2023; Pena et al., 2021; Attia et al., 2013). In process planning and simulation, AI automates the optimization of manufacturing parameters, tool paths, and production schedules, ensuring efficient and effective manufacturing workflows. Robotic manufacturing and assembly are greatly enhanced by AI, with AI-powered robotics performing precise tasks such as material handling, layup, and inspection. This automation improves both productivity and quality. In additive manufacturing (AM), AI optimizes processes for composites, enhancing part quality, accuracy, and performance, and enabling rapid prototyping and customization.

AI-driven systems also automate quality control and defect detection, ensuring real-time monitoring and reducing scrap rates by quickly identifying and addressing defects. Predictive maintenance benefits from AI's ability to analyze equipment data to predict failures and schedule proactive maintenance, thereby minimizing downtime. In supply chain management, AI optimizes inventory management, procurement, and logistics, reducing lead times and mitigating risks (Mittal, 2023; Modgil et al., 2022)

Continuous improvement is facilitated by AI-driven analytics and optimization, which continuously refine processes to enhance efficiency, quality, and sustainability. By integrating AI into various aspects of manufacturing, the composite material engineering field experiences significant advancements in automation, leading to more efficient, cost-effective and high-quality production processes.

5.3 Sustainable Materials Development

Case studies and examples AI accelerates sustainable materials development in composite engineering by optimizing compositions, processes, and recycling efforts. Through materials informatics and design optimization, AI analyzes large datasets to identify and optimize environmentally friendly material alternatives. AI quantifies environmental impact throughout the material life cycle with life cycle assessment (LCA), guiding design and process improvements (Fnais et al., 2022).

AI also designs composites for easier recycling and circularity, promoting resource conservation and waste reduction. By optimizing manufacturing processes, AI minimizes waste and improves material efficiency. Additionally, AI reduces energy consumption and optimizes resource use in manufacturing processes, contributing to energy efficiency and resource conservation. Ensuring compliance with environmental regulations and standards, AI provides analysis and monitoring capabilities. Predictive modeling allows AI to forecast material properties and environmental impacts, facilitating the development of sustainable composites with tailored properties.

AI-driven approaches in automation and sustainability foster innovation and advancement in composite material engineering, steering the industry towards a more efficient, productive, and environmentally friendly future (Wan et al., 2020), Including case studies and examples provides concrete evidence of AI's impact on composite material engineering. In aerospace, Airbus uses AI to monitor composite components in aircraft, predicting maintenance needs based on wear and fatigue patterns. This approach reduces downtime and extends material lifespan. In the automotive industry, BMW employs AI to analyze material databases and simulations, identifying high-performance composites for vehicle components (Koronis et al., 2013). This accelerates material discovery, enhancing fuel efficiency and reducing emissions (Winkler, 2023).

AI also plays a crucial role in quality control for wind turbine blades, as demonstrated by Vestas (Mitchell, 2022). By using AI-driven computer vision to inspect wind turbine blades, Vestas can detect defects early and ensure reliability through proactive maintenance (Khallaf, 2024). In the area of sporting goods, Wilson Sporting Goods leverages AI to optimize composite materials in athletic equipment, improving performance and durability in products like tennis rackets (Edriss, 2024).

Process control in marine manufacturing benefits significantly from AI as well. Sunseeker International utilizes AI to optimize resin infusion during boat hull fabrication, ensuring uniformity and quality in composite structures. Similarly, in the construction industry, Skanska applies AI to streamline procurement and logistics for composite building materials, reducing lead times and waste, and enhancing project efficiency (Sawhney, 2020).

AI's predictive modeling capabilities are harnessed by different studies to predict the mechanical properties and behavior of composite materials, accelerating design and optimization for various applications (Li et al., 2024; Batra, et al., 2021; Guo et al., 2021). These examples illustrate AI's diverse applications across predictive maintenance, materials discovery, quality control, design optimization, process control, supply chain optimization, and predictive modeling, highlighting its transformative potential in composite material engineering.

6. AI Applications in Composite Material Research and Development

AI has significantly transformed composite material engineering by enhancing design, manufacturing, and optimization processes. One notable application is in materials discovery and design optimization, exemplified by Citrine Informatics, which uses AI to analyze extensive material property databases (Ward et al., 2018). This enables the identification of optimal composite material compositions and structures, accelerating the development of advanced materials for sectors such as aerospace, automotive, and renewable energy (Himanen et al., 2019).

In process optimization and simulation, Autodesk's Fusion 360 integrates AI to optimize parameters, tool paths, and material usage in composite manufacturing (Pires et al., 2022). This integration enhances workflow efficiency, reduces costs, and improves component quality (Henning, 2019). Similarly, in quality control and defect detection, GE Aviation employs AI-driven systems to inspect composite aircraft engine components. AI analyzes high-resolution images to detect defects like voids and delaminations, ensuring component reliability and safety (Wang et al., 2022).

AI also plays a crucial role in predictive maintenance and reliability analysis. Siemens Digital Industries uses AI to analyze sensor data and maintenance records, predicting equipment failures and suggesting maintenance actions (Annanth, et al., 2021). This approach improves equipment reliability and reduces maintenance costs (Souza et al., 2020). In structural health monitoring and damage assessment, NASA utilizes AI for real-time monitoring of composite structures in aerospace applications (Elenchezhian et al., 2021). AI analyzes sensor data to detect damage and fatigue, ensuring the safety and reliability of structures like aircraft wings (Alvarez-Montoya et al., 2020).

Environmental impact assessment and sustainability analysis benefit from AI as well. BASF employs AI to evaluate the sustainability of composite material production, analyzing life cycle data and energy consumption to identify ways to improve resource efficiency and reduce environmental impact. Additionally, in materials characterization and property prediction, Stanford University's Materials Genome Initiative uses AI to predict composite material properties with high accuracy (Sha et al., 2020). By combining experimental data and computational models, AI accelerates the development of high-performance materials (Pyzer-Knapp et al., 2022).

7. Conclusion

This review explored the intersection of Artificial Intelligence (AI) and composite material engineering, identifying the profound opportunities and significant challenges that lie ahead. AI technologies offer transformative potential for enhancing material design, optimizing properties, and improving manufacturing processes in composite material engineering. Despite the hurdles in data acquisition, model interpretability, and integration into existing workflows, the strategies outlined in this research pave the way for overcoming these challenges. By leveraging interdisciplinary collaboration, robust data governance, and continuous innovation, the field can unlock new levels of performance and sustainability in composite materials. As we move forward, embracing AI's capabilities will be crucial for driving advancements, fostering responsible innovation, and ensuring the future success of composite material engineering.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Onyeka Augustine Umeliwu, Bassey Okon Samuel;* ***data collection:*** *Onyeka Augustine Umeliwu;* ***analysis and interpretation of results:*** *Onyeka Augustine Umeliwu, Bassey Okon Samuel;* ***draft manuscript preparation:*** *Onyeka Augustine Umeliwu, Bassey Okon Samuel. All authors reviewed the results and approved the final version of the manuscript.*

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