

REVIEW ARTICLE

A comprehensive review of artificial intelligence applications in composite materials: Predictive, generative, and automation approaches

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Abstract

The rapid advancement of artificial intelligence (AI) has led to its widespread adoption across various engineering fields, including composite materials research. Composite materials, known for their superior mechanical properties and lightweight characteristics, play a crucial role in industries such as aerospace, automotive, and robotics. However, their inherent complexity—such as anisotropic behavior, nonlinear characteristics, and intricate microstructures—poses significant challenges for traditional design and analysis methods. To address these challenges, AI-driven approaches have emerged as powerful tools, offering solutions in prediction, generation, and automation. This review systematically explores applications of machine learning and deep learning in composite materials research, categorized into three major approaches: predictive, generative, and automation models. Predictive models enhance the accuracy of property prediction and microstructure analysis. Generative models facilitate novel material discovery and microstructure design. Automatic models improve quality control and can be used to optimize manufacturing processes through real-time data analysis. By leveraging diverse large-scale datasets, AI provides innovative solutions to the key challenges associated with composite materials and enhances research and design efficiency. This review highlights the transformative potential of AI in composite materials research, providing insights into future research directions and challenges.

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1. Introduction

Since the emergence of AlphaGo, artificial intelligence (AI) technology has rapidly advanced over the past decade, alongside the development of graphics processing units (GPUs) for parallel computing.^{1,2} AI technology has recently reached a level where it is easily accessible in daily life, as demonstrated by the widespread adoption of generative conversational AI models, such as ChatGPT.^{3,4} Furthermore, AI is now a core technology driving innovation across various engineering industries, including autonomous driving, biotechnology, robotics, aerospace, semiconductors, and composite materials.⁵⁻¹²

Composite materials are engineered by combining multiple constituent materials to achieve properties superior to those of conventional materials. The exceptional

lightweight characteristics and outstanding mechanical performance of composite materials make them essential in various industries, including aerospace, automotive, energy harvesting, robotics, and construction, as shown in Figure 1.¹³⁻¹⁹ The properties of composite materials are influenced by multiple factors, including the types of fiber and resin, as well as the manufacturing process. In addition, their inherent anisotropy, nonlinearity, and complex microstructure make design and analysis significantly more challenging than conventional materials.

Traditionally, the field of composite materials has relied heavily on the expertise of skilled professionals for conducting experiments and developing physics-based models. In addition, simplifying assumptions have often been used to simulate the complex behavior of composite materials. However, these conventional approaches have clear limitations in fully capturing the intricate and diverse characteristics of composite materials. As a result, machine learning (ML) and deep learning (DL) methodologies have recently received significant attention in the field of composite materials. ML is increasingly being explored to overcome the challenges associated with traditional methods, offering new possibilities for improving efficiency and accuracy in the design, analysis, and manufacturing of composite materials.

The applications of ML in the field of composite materials, as illustrated in Figure 2, can be broadly categorized into three aspects:

- (i) Prediction: ML enables the analysis of large-scale datasets to uncover complex patterns in areas such as mechanical property and behavior prediction, and design parameter estimations^{20,21}
- (ii) Generation: ML leverages data-driven learning to construct new information, such as for

microstructure design, novel material discovery, and data augmentation²²

- (iii) Automation: ML is applied to optimize composite manufacturing processes, automate defect detection and quality control, and analyze real-time data to enhance manufacturing efficiency.²³

AI thus serves as a powerful tool for addressing various challenges in the field of composite materials, significantly enhancing research and design efficiency. However, the use of insufficient or unreliable data, as well as the application of unsuitable ML techniques, can lead to suboptimal results or computational inefficiencies.

Therefore, a structured and systematic understanding of ML applications in the field of composite materials is essential. To address this need, this review provides a comprehensive and systematic analysis of ML-driven research on composite materials. The primary contributions of this paper are threefold. First, we propose a clear and structured classification of ML applications for composite materials into three categories: predictive, generative, and automation models. Second, we provide an in-depth review of the state-of-the-art ML techniques within each category, focusing on their practical applications in composite material design, manufacturing, and analysis. Third, we critically discuss the current limitations and challenges of these ML approaches and propose future research directions to address them.

The remainder of this paper is organized as follows: sections 2, 3, and 4 provide detailed discussions on the applications of predictive, generative, and automation models, respectively, in the field of composite materials. Finally, Section 5 presents the key findings, highlights the current limitations, and outlines future research directions for advancing AI-driven developments in this field.

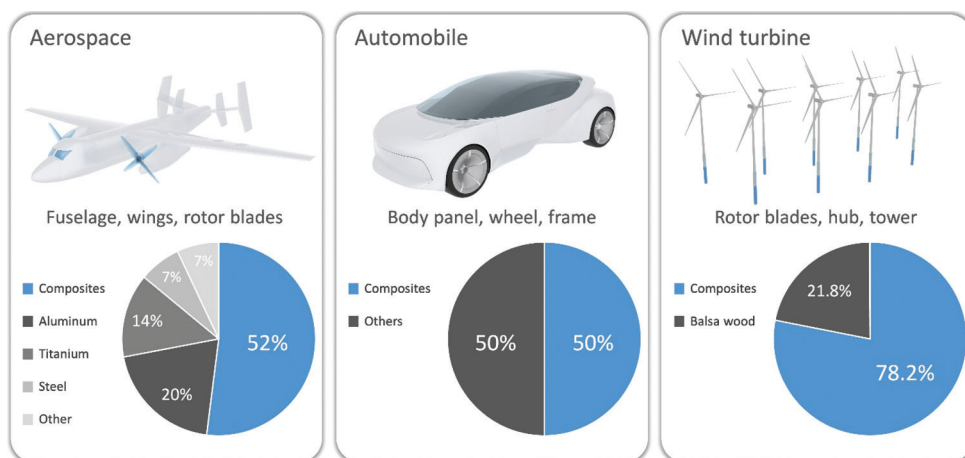


Figure 1. Components made of composite materials and the proportions (by weight) of different materials used in the aerospace, automobile, and wind turbine industries¹⁷⁻¹⁹

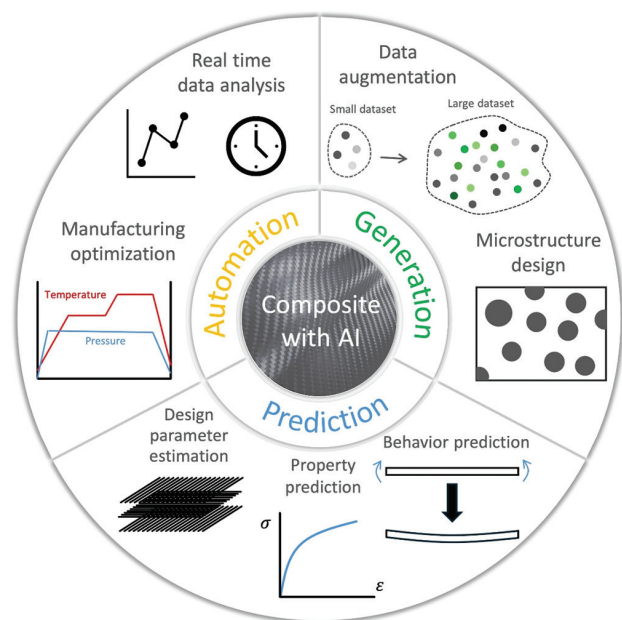


Figure 2. Machine learning applications in composite materials research: prediction, generation, and automation
Abbreviation: AI: Artificial intelligence.

2. Predictive models for composite materials

Predictive ML models are designed to estimate output properties or behaviors based on the given input data by identifying complex patterns and relationships. In the field of composite materials, predictive models play a crucial role as traditional experimental and numerical methods for property prediction can be time-consuming and computationally expensive, especially when dealing with the anisotropic and nonlinear nature of composites. By leveraging ML models trained on extensive datasets, predictive models enable rapid and reliable predictions, significantly enhancing efficiency in material design, performance evaluation, and failure analysis. This section will explore different ML models and techniques used for prediction in composite materials research.

2.1. Deep neural networks (DNNs)

An artificial neural network (ANN) is a type of ML technology inspired by the human nervous system. It serves as a mathematical model for learning information from the given data and recognizing patterns.^{24,25} A DNN, as shown in [Figure 3A](#), is a specialized form of ANN that incorporates multiple hidden layers, allowing for the extraction of complex features from data.²⁶⁻²⁸ While the concept of ANNs has been around for decades, the advancement of GPU technology has enabled the practical implementation of DNNs, leading to significant

breakthroughs in DNN research and applications. Because of their deep architecture, DNNs excel at capturing intricate patterns and relationships, making them particularly effective in handling nonlinear data and solving complex problems. When trained with sufficient, high-quality data, highly accurate predictions can be made for the given inputs, making it a powerful tool for data-driven analysis in various domains.

With the advancement of DNN technology, its applications in the field of composite materials have been steadily expanding. Traditional analytical methods often rely on various assumptions and simplifications that require extensive computational resources and time. However, by learning from large-scale datasets, DNNs can efficiently and accurately predict the behavior and properties of composite materials, overcoming the limitations of traditional methods in terms of speed and precision.

DNNs have been effectively utilized to predict the nonlinear responses and complex characteristics of composite structures, such as composite springs, composite tubes, and bistable composite structures, which are difficult to analyze analytically.^{29,30,33} Zhang *et al.*³³ applied a DNN-based surrogate model to analyze the behavior of deployable bistable composite structures with C-cross sections, using finite element analysis (FEA) data for training and subsequently performing structural optimization. Similarly, as shown in [Figure 3B](#), Hong *et al.*²⁹ utilized DNNs to predict ground reaction forces using self-sensed capacitance data from composite ankle springs, enabling the extraction of running parameters for exo-robot applications. Wang *et al.*³⁰ developed a DNN-based surrogate model to predict the mechanical properties of braided-textile reinforced tubular structures. [Figure 3C](#) shows the performance and error of the predicted results (peak force, mean crushing force, displacement corresponding to peak force, and effective compression stroke). In addition, as shown in [Figure 3D](#), a DNN was utilized to predict the transverse mechanical response of unidirectional fiber-reinforced composites, incorporating the effects of defects, such as matrix voids and fiber-matrix debonding.³¹ Their approach used an experimentally validated discrete element method model to generate training data of crack initiation and propagation at the particle-level in representative volume elements (RVEs) of the composite. The trained DNN predicted the initial crack location and the corresponding stress at the onset of cracking with accuracies of 82% and 94%, respectively. DNNs were integrated with the Abaqus FEA code by Tao *et al.*³⁴ to learn composite constitutive laws, ensuring physical consistency and enabling accurate, data-driven structural predictions. Furthermore, DNNs were used for

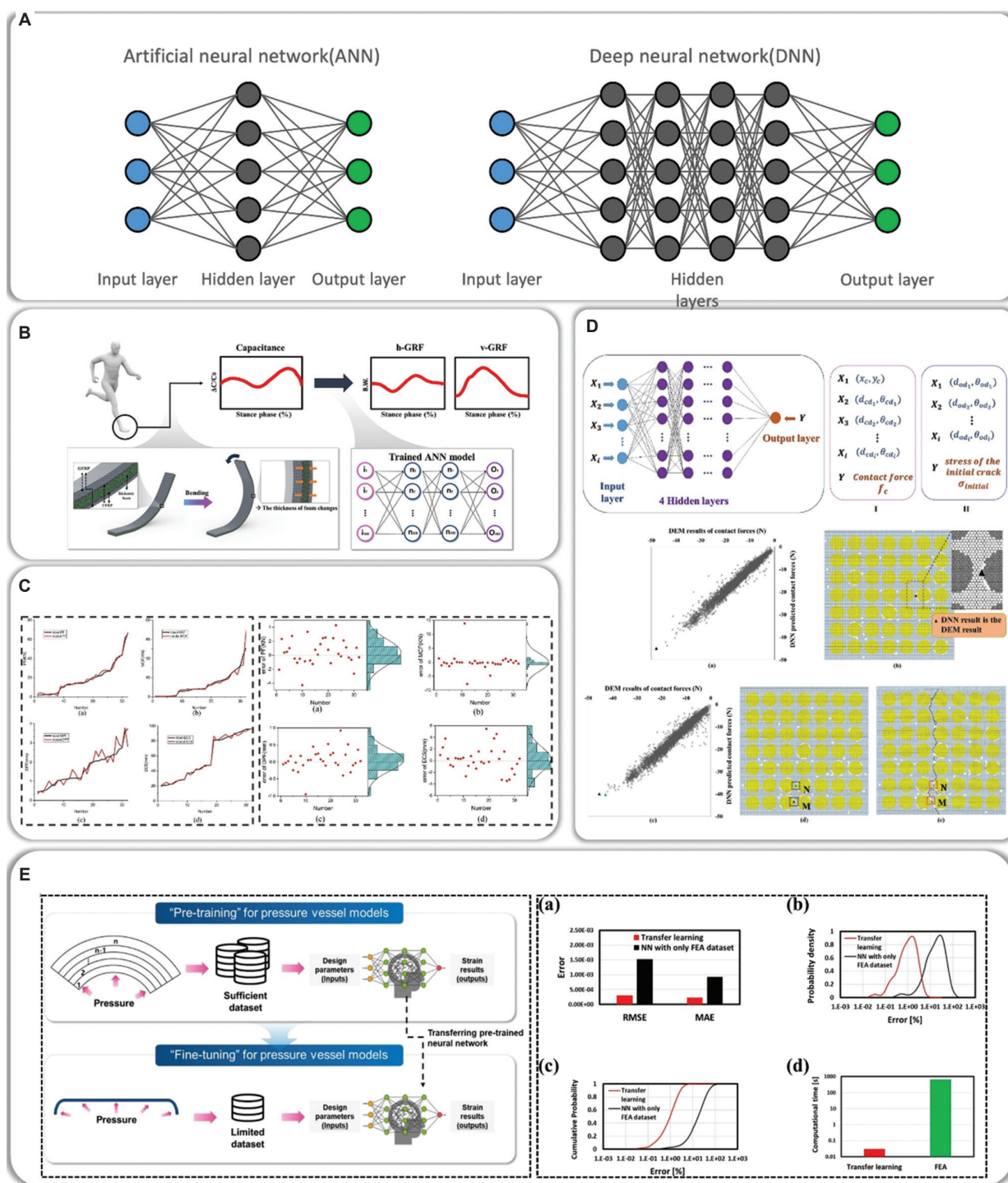


Figure 3. DNNs for composite materials prediction. (A) Structure of ANN and DNN; (B) A schematic illustrating the use of a DNN to predict ground force by applying capacitance-based self-sensing of the foam core in a sandwich composite.²⁹ Reprinted with permission from Hong *et al.*²⁹ Copyright © 2022 Elsevier; (C) Prediction results (peak force, mean crushing force, displacement corresponding to peak force, and effective compression stroke) and errors for braided-textile reinforced tubular structures.³⁰ Reprinted with permission from Wang *et al.*³⁰ Copyright © 2021 Elsevier; (D) Prediction results of macroscopic stiffness and yield strength of unidirectional fiber composites using DNN;³¹ (E) Training process of transfer learning for predicting the behavior of composite pressure vessels and comparison with conventional finite element analysis methods.³² Reprinted with permission from Hong *et al.*³² Copyright © 2024 Elsevier.

Abbreviations: ANN: Artificial neural network; DEM: Discrete element method; DNN: Deep neural network; FEA: Finite element analysis; GRF: Generalized random forests; MAE: Mean absolute error; NN: Neural network; RMSE: Root mean squared error.

permeability prediction, in which statistical RVEs with randomized fiber distributions were generated specifically for training DNNs to address the stochastic nature of fibrous microstructures.³⁵

These examples highlight the significant impact of DNNs on the research of composite materials. DNNs enable accurate predictions and efficient calculations, capturing complex structural responses that are challenging to model with traditional methods. By learning from large datasets, DNNs provide a reliable alternative or complement to numerical methods, such as FEA, offering data-driven insights and improved speed and precision when optimizing composite materials and structures. However, DNNs face significant limitations when there is insufficient data or when the model encounters conditions different from those in the training dataset. In such cases, transfer learning techniques serve as a powerful tool to overcome these challenges.³⁶⁻³⁸ By applying the knowledge (such as network weights and feature representations) obtained from a pre-trained model to a new related problem, transfer learning accelerates training, improves performance, and enables effective learning even with limited data. For example, transfer learning has been applied to predict the behavior of composite pressure vessels by combining analytical and numerical data, significantly enhancing both accuracy and computational efficiency.³² As presented in [Figure 3E](#), the approach involves pre-training on a large-scale analytical dataset with relatively low fidelity but low cost, and then fine-tuning with a smaller-scale numerical dataset that offers higher fidelity but at a higher cost. This strategy enables the rapid assessment of structural integrity under various loading conditions, reducing the need for time-consuming finite element simulations.

2.2. Convolutional neural networks (CNNs)

A CNN is a type of DL model specifically designed for image processing and analysis.³⁹⁻⁴¹ Unlike general DNNs, CNNs are highly effective at handling image-based data, making them particularly advantageous for visual data-related problems. As illustrated in [Figure 4A](#), CNNs use convolutional and pooling operations to efficiently extract important features from input data, reducing the need for manual feature engineering. CNNs have demonstrated exceptional performance in various vision tasks, including image classification, object detection, and facial recognition.⁴²⁻⁴⁴

In the field of composite materials, microstructure analysis and fiber orientation prediction are often difficult to conduct using conventional analytical methods or general DNNs.^{48,49} Taking advantage of the superior pattern recognition capabilities of CNNs, image data of composite materials can be utilized to predict microstructures

and material behavior, making CNNs essential when considering image-based composite material problems.

CNNs have been successfully applied to various aspects of composite material analysis.^{45,46,50-52} Key characteristics, such as the fiber arrangement, fiber diameter, and resin content, can be extracted from microstructure images using CNNs, which can then be used to predict the mechanical behavior and failure mechanisms of composite materials. As shown in [Figure 4B](#), CNN-based models have been employed to predict the stacking angles of fiber-reinforced composites from cross-sectional images.⁴⁵ Extracting composite stacking information is particularly valuable for the reverse-engineering of composite material structures, as the performance of fiber-reinforced composites is highly sensitive to stacking angles.

U-Net architectures, which are built on CNNs, have been used to predict stress fields within composite microstructures by using stress maps generated from FEA as training data.⁵⁰ U-Net models provide a computationally efficient alternative to traditional simulations, reducing the computational burden of multi-scale modeling while maintaining high levels of predictive accuracy.

In addition to stress field and stacking angle predictions, CNNs have been applied to estimate the mechanical properties of composite materials, such as the transverse modulus, tensile strength, and fracture toughness, based on microstructural images using finite element simulation results as training data.⁵¹ By training on a large dataset of RVEs, these models can capture complex material behaviors and improve the accuracy of property estimation.

Moreover, as shown in [Figure 4C](#), CNN-based approaches have been successfully implemented for efficient prediction of the 3D permeability of fibrous microstructures by integrating 2D image-based learning with circuit analogy models.⁴⁶ The permeability is a crucial factor in composite material manufacturing since it affects the ability of the fibrous reinforcement to achieve complete impregnation during the resin infusion process. The use of CNNs not only accelerates the permeability prediction process but also enhances the overall understanding of fluid flow in porous composite media.

These studies highlight the transformative potential of CNNs in composite materials research, offering new possibilities for advanced composite structures through enhanced image-based analysis and prediction. However, despite the effectiveness of CNNs, one limitation is the challenge of acquiring sufficient training data. Specifically, collecting high-quality images of composite materials is difficult, which limits the model's learning process. In addition, CNN-based approaches require extensive pre-processing of image data, increasing the complexity of implementation.

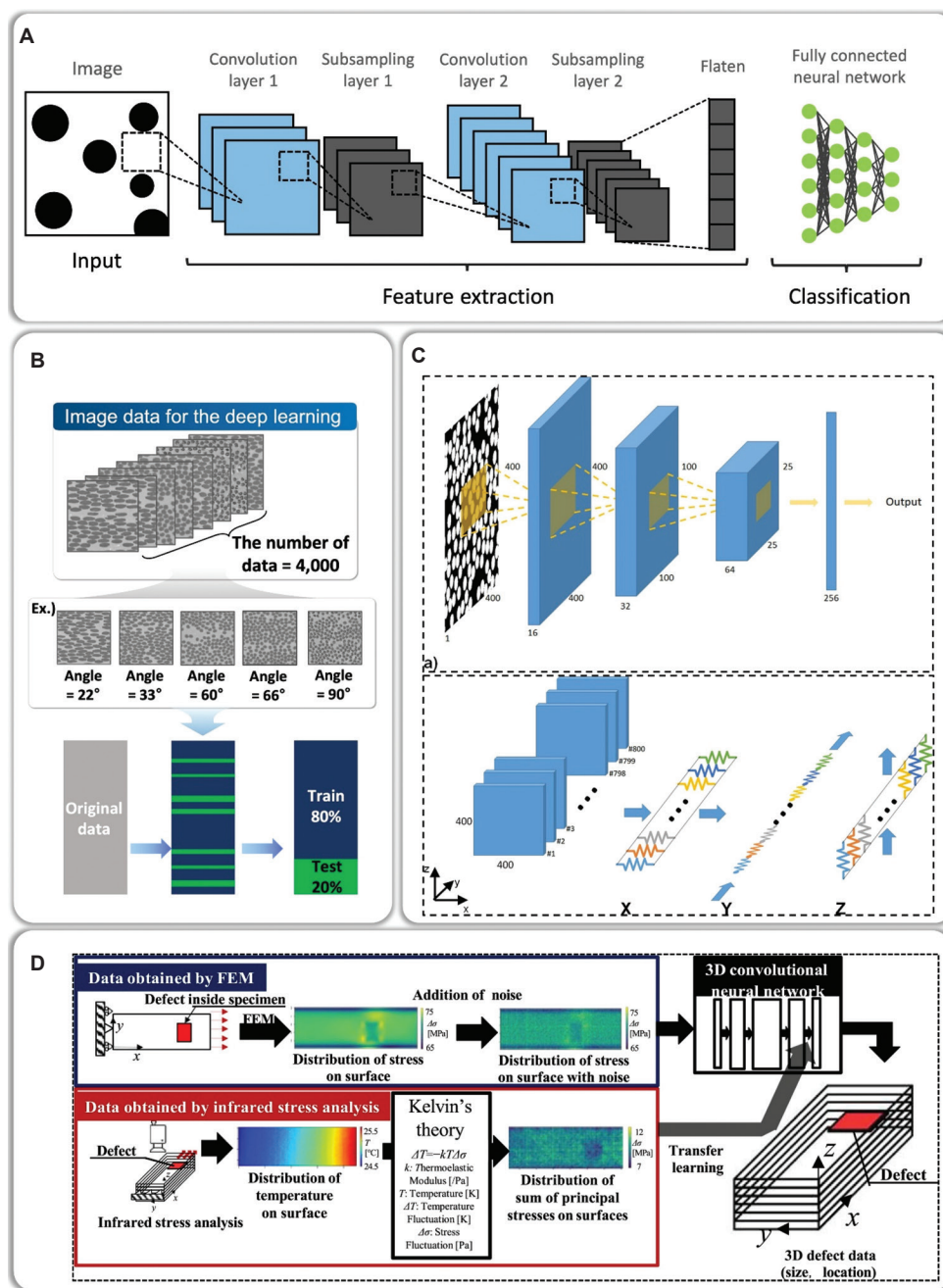


Figure 4. CNN architecture and research utilizing CNN in the field of composite materials. (A) Structure of CNN; (B) Image data and data classification process for predicting stacking angle based on cross-sectional images;⁴⁵ (C) CNN architecture and circuit analogy configuration used for estimating the principal permeability values of the considered 3D fibrous structures;⁴⁶ (D) Ground truth of defects for each layer of the composite laminate and the predicted results.⁴⁷

Abbreviations: CNN: Convolutional neural network; FEM: Finite element method.

To address these challenges, data augmentation techniques, such as rotation, distortion, and noise addition, can be used to enhance the training dataset.^{53,54} For example, Shim *et al.*⁵⁵ applied CNN and data augmentation to predict the stress-strain curves of composites fabricated through mechanical recycling, enabling effective learning

even with a limited dataset. In this process, each image was rotated by 90°, 180°, and 270°, and then horizontally flipped to generate eight images per single specimen. Generative models, discussed in the next section, can also be used for data augmentation to obtain more diverse images and further enhance training efficiency.⁵⁶⁻⁵⁸

Similarly, as with DNNs, many studies have also utilized transfer learning techniques to enhance the training efficiency of CNNs. Kojima *et al.*⁴⁷ used transfer learning with CNNs to predict internal defects in carbon fiber-reinforced polymer (CFRP) laminates by combining data generated through FEA with infrared stress distributions obtained from experiments. Figure 4D presents the ground truth of defects for each layer of the composite laminate, together with the predicted results obtained through transfer learning. By fine-tuning these models with a limited set of experimental data, transfer learning improves their generalization capabilities across various composite structures. The results show that as the amount of experimental stress measurement data increases, transfer learning-based defect prediction outperforms traditional FEA-based approaches in terms of efficiency. Moreover, Liu *et al.*⁵⁹ aimed to diagnose damage in composite materials using transfer learning with CNNs by leveraging Lamb wave signals generated from numerical simulations and applying them to experimental data. By integrating transfer learning with domain adversarial learning, the model achieved high generalization performance across complex domain discrepancies, leading to highly accurate delamination prediction. In addition to cases of domain adaptation, where only the domains differ while the tasks remain the same as in the aforementioned studies, transfer learning can also be applied when there are differences in the source and target tasks. Xu *et al.*⁶⁰ extracted vector representations of the geometric morphology and distribution characteristics of two-phase composites from images to establish similarity between the source and target domains. Their method enabled the use of small datasets through transfer learning, yielding high prediction accuracy for mechanical properties, such as stiffness, strength, and toughness. Techniques such as data augmentation and transfer learning not only enhance the efficiency of predictive models but also enable broad applicability across diverse tasks and DL models.

In addition, developing hybrid models by integrating CNNs with other ML/DL methods holds promise for enhancing their ability to capture and analyze complex composite material structures.⁶¹⁻⁶⁴ Among various approaches, attention mechanism-based CNNs have demonstrated strong capabilities in capturing complex failure behaviors. Liu *et al.*⁶⁴ incorporated an attention-based loss function into a CNN framework, enabling the model to focus more on high-damage regions in thick composites with wrinkles, thereby achieving effective prediction of failure modes.

2.3. Recurrent neural networks (RNNs)

RNNs are a type of DL model designed to process sequential data, and they excel in handling data that contain temporal

or spatial-order relationships. Unlike feedforward neural networks or CNNs, RNNs receive data one step at a time in sequential order, as shown in Figure 5A, and have feedback connections in the hidden layers to recognize the sequential structure of the data. This architecture is advantageous in problems where the order of inputs is important, and it also offers the flexibility to handle variable-length data. However, RNNs have a drawback known as the long-term dependency problem, where the influence of distant inputs diminishes over time despite their relevance. In addition, as weights are multiplied across time steps, the model suffers from vanishing or exploding gradient issues. To address these problems, advanced RNN-based models, such as long short-term memory (LSTM) and gated recurrent unit (GRU), are commonly used (Figure 5A). LSTM utilizes three gates to selectively store, transmit, and discard information, and uses a memory cell to retain long-term data. GRU, a simplified version of LSTM, applies an update gate to determine how much of the previous information to keep, and a reset gate to decide how much of the past information to forget, thereby overcoming the limitations of conventional RNNs.

Since composites exhibit highly nonlinear and time-dependent behavior, RNNs have been actively studied and applied in various research areas.^{65,66,70-76} Chen *et al.*⁷⁰ predicted the nonlinear behavior of composites, such as the time-dependent nonlinear elastic-plastic response that varies with the strain/loading path, using an LSTM network capable of processing the entire time sequence. As a result, the trained LSTM model accurately predicted stress with a maximum error of <4%, and the model successfully reproduced the stress-strain hysteresis curves even under nonlinear cyclic loading conditions. Yousefi *et al.*⁶⁵ also employed an LSTM DL model, as shown in Figure 5B, to predict the long-term water absorption and thickness swelling behavior of a composite composed of hydrophilic cellulose fibers and hydrophobic polypropylene. By training the model with the initial 200 h of data obtained from immersion experiments, they demonstrated that the LSTM can effectively predict the long-term physical behavior of the composite for the subsequent 1300 h. Furthermore, RNN-based models have also been utilized to predict the behavior of composites under dynamic loading conditions. Borkowski *et al.*⁷¹ employed a GRU to predict the response of ceramic matrix composites (CMCs) under non-monotonic loading and microstructural variations, and demonstrated that stable predictions could be achieved without overfitting across 60 test sets. Gao *et al.*⁶⁶ applied an LSTM to predict the axial stress of concrete-granite composites under impact conditions, as shown in Figure 5C. The trained model was able to predict stress responses to new impact velocities, joint roughness

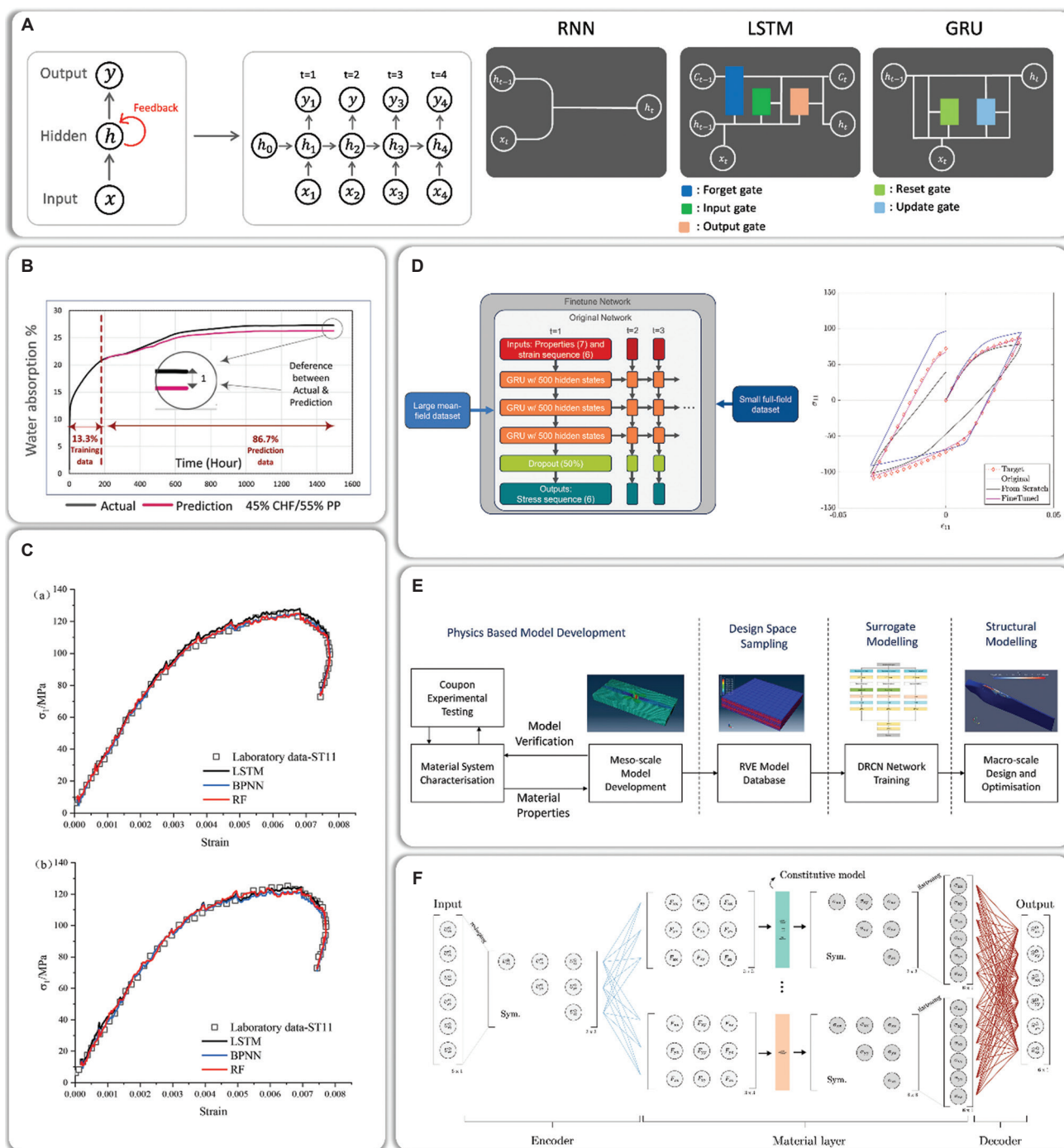


Figure 5. RNN, LSTM, and GRU architectures and research utilizing RNN in the field of composite materials. (A) Structure of RNN, LSTM, and GRU; (B) Comparison of actual and predicted results of water absorption;⁶⁵ (C) Comparison between the actual and predicted stress values;⁶⁶ (D) Network architecture and the transfer learning approach utilizing a large mean-field and a small full-field data set;⁶⁷ (E) Overview of data-driven multiscale framework using DRCN networks;⁶⁸ (F) Architecture of PRNN for finite strain framework.⁶⁹ Abbreviations: BPNN: Backpropagation neural network; CHF: Corn husk fiber; DRCN: Decomposing residual convolutional neural; GRU: Gated recurrent unit; LSTM: Long short-term memory; PP: Polypropylene; PRNN: Physically recurrent neural network; RF: Random forest; RNN: Recurrent neural network; RVE: Representative volume element.

coefficients, and strain inputs, and showed improved prediction accuracy compared to backpropagation neural network and random forest models. RNNs have also been employed to predict the shape transformation of 4D-printed active composite structures. Sun *et al.*⁷³ designed an active composite beam using materials with different coefficients of thermal expansion and treated the material distribution as sequential data. By applying an RNN model, they successfully predicted the resulting shape under a stimulus of a 100°C temperature increase, achieving over 2000 times faster performance compared to conventional finite element simulations. In addition, to enhance the performance of RNNs, bidirectional RNNs – which process input sequences in both forward and backward directions – have been employed in studies to identify the location and size of defects in laminated composites⁷⁷ and to efficiently predict the time-dependent damage of composite hydrogen tanks.⁷⁸

However, RNNs require a large amount of data for training and are difficult to capture spatial patterns compared to CNNs. To address these limitations, recent studies have explored combining RNNs with techniques such as transfer learning^{67,79-82} and CNNs.^{68,83-85} Cheung *et al.*⁶⁷ combined transfer learning with a GRU-based DL model to reduce the computational cost of predicting the nonlinear elasto-plastic behavior of short fiber reinforced composites, as shown in [Figure 5D](#). In this approach, a mean-field-based RNN model was used with low-fidelity samples, while high-fidelity full-field simulation data were employed for fine-tuning. As a result, they successfully developed a framework with excellent computational efficiency and generalization performance. Jian *et al.*⁸⁰ also employed a combination of bidirectional LSTM and transfer learning to predict the behavior of CFRP composites in the very high cycle fatigue regime. In their approach, transfer learning was applied to predict the fatigue behavior of a new batch by leveraging existing experimental data. An attention mechanism was incorporated to focus on critical segments of the fatigue curve, such as regions with abrupt changes, thereby improving prediction accuracy and convergence speed. However, attention mechanisms, while advantageous for highly complex, imbalanced, or long-dependency data, may lead to overfitting and increased computational time when applied to low-complexity or relatively uniform data.⁷⁸ Therefore, careful consideration of the characteristics of the data is essential when applying attention mechanisms. As shown in [Figure 5E](#), El Said⁶⁸ employed a deep recurrent CNN that combines CNN and LSTM to predict the nonlinear damage behavior of laminated composite structures. In particular, since features such as layup configuration, wrinkles, and ply gaps exhibit spatial characteristics, a CNN was used to

extract spatial information from RVE images, which was then converted into sequences and fed into the LSTM to predict the stress at each time step. CNN-RNN-based models have also been applied to predict the evolution of surface roughness in carbon/carbon composites under thermochemical ablation⁸³ and to assess damage in composites subjected to low-velocity impacts.⁸⁵ According to a study by Truong *et al.*,⁸⁴ combining CNN with GRU yielded the highest prediction accuracy compared to using CNN, RNN, GRU, or LSTM individually.

Moreover, traditional RNNs are less robust to new conditions due to the absence of physically derived patterns, which prompted a series of studies to explore physically RNN (PRNN) models that incorporate physical constraints directly into the RNN architecture.^{69,86} Maia *et al.*⁶⁹ aimed to predict the path- and rate-dependent stress responses of composites by embedding the constitutive models into the material layer of the PRNN, as shown in [Figure 5F](#). This approach enabled them to incorporate the non-linear elasto-viscoplastic, path- and rate-dependent behavior of the matrix, as well as the nonlinear elastic and anisotropic characteristics of the fibers, into the RNN architecture. As a result, the model accurately predicted stresses with a mean absolute error of 5–7 MPa and a relative error within 5–10% under various loading conditions, and was also used to successfully extrapolate to loading conditions not included in the training data.

2.4. Physics-informed neural networks (PINNs)

DNNs accurately represent the relationship between the given inputs and outputs based on large-scale labeled datasets. However, due to their purely data-driven learning approach, the relationship itself remains a black box, which may limit their ability to reflect physical phenomena reliably. In contrast, PINNs integrate physical laws into the neural network learning process, as shown in [Figure 6A](#).^{87,88} PINNs do not require any labeled (input-to-output) data for training, and the governing partial differential equation (PDE), as well as initial and boundary conditions that describe the process being modeled, are used to train the neural network.

In the case of composite materials, solving the various PDEs that describe the elastic behavior, heat transfer, and damage or fracture models through FEA is time-consuming, and ML-based predictions often fail to reflect real physical phenomena. In contrast, predictions generated by PINNs can be consistent with the specified physical laws, even outside the training domain, making PINNs a powerful tool for efficiently predicting complex phenomena in composites research, such as plastic deformation, flow through porous media, and heat

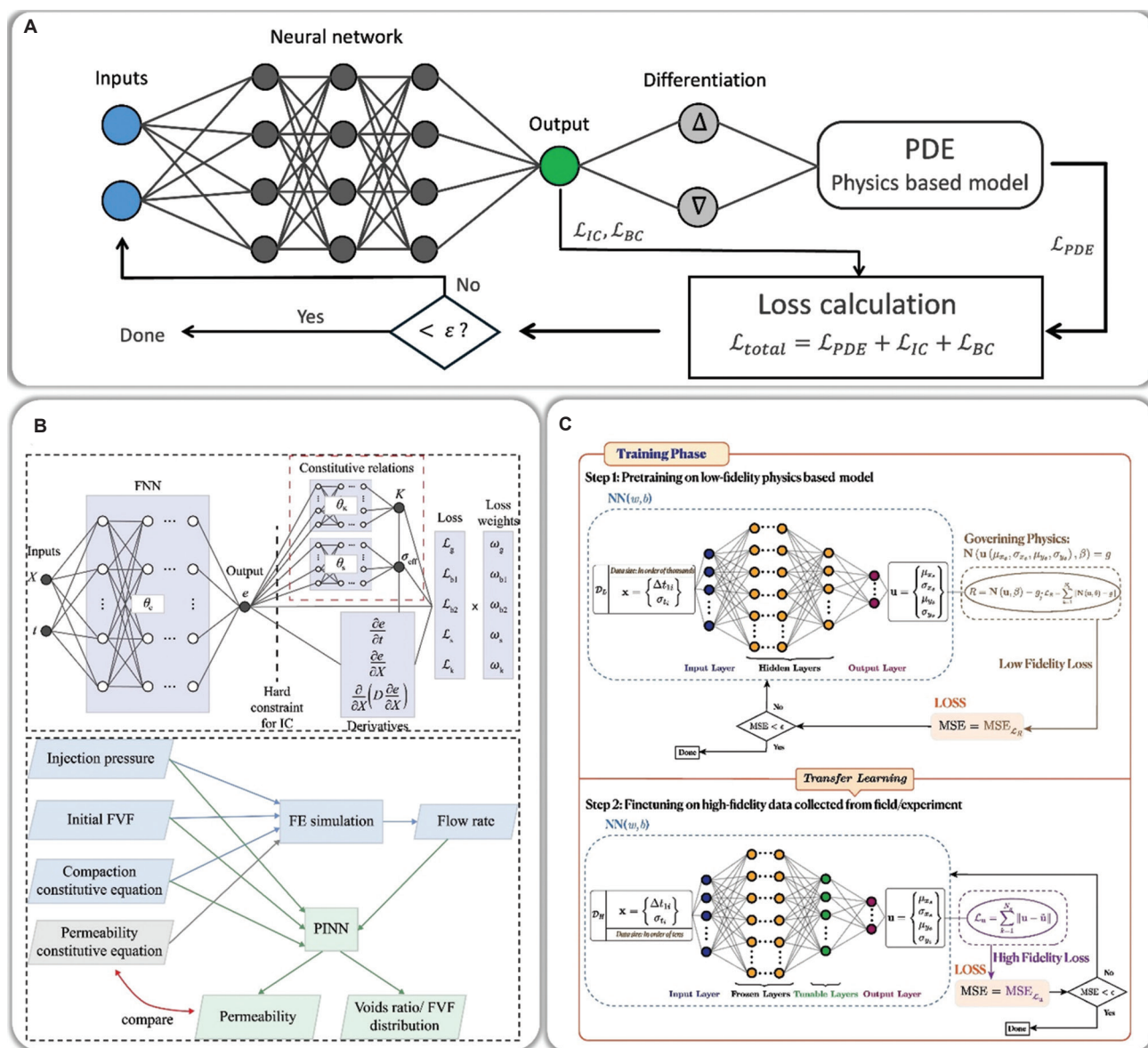


Figure 6. Structure of PINNs and research utilizing PINNs in the field of composite materials. (A) Structure of PINNs; (B) PINN framework and prediction results for estimating FVF distribution and permeability during injection-based measurements;⁸⁹ (C) multi-fidelity PINN framework for predicting defect positions in composites.⁹⁰

Abbreviations: FE: Feature engineering; FNN: Forward neural network; FVF: Formation void fraction; MSE: Mean squared error; NN: Neural network; PDE: Partial differential equation; PINN: Physics-informed neural networks.

transfer. In addition, PINNs do not require meshing of the solution domain, and parameterized PDEs can be solved by including the process parameters directly as inputs to the neural network. Thus, PINNs can be utilized as accurate, time-efficient, data-free surrogate models for rapid process optimization.

Several studies have successfully applied PINNs for analyzing composite materials.⁸⁹⁻⁹⁵ Using PINNs, researchers successfully predicted the composition-property relationships of basalt fibers, which are known

for their mechanical and thermal stability.⁹² Compared to traditional ANNs, the PINN model exhibited significantly improved predictions of the elastic modulus and tensile strength. This improvement highlights the PINN’s advantage in incorporating physical constraints into the learning process to enhance the model’s predictive accuracy.

Moreover, PINNs have also been applied to predict property degradation in carbon fiber/epoxy composites exposed to high-intensity radiative environments, such as weapon-induced explosions and solar flux.⁹⁵ The model

demonstrated high precision and reliability, with errors in the order of 10^{-5} . Compared to conventional numerical methods, such as the finite element method and finite difference approaches, the PINN framework reduced the computation time by over an order of magnitude.

To better represent the response of real fibrous reinforcements, Lee *et al.*⁸⁹ incorporated experimental data of the permeability and compressibility relations into the PINN training process to explain the remaining physics not expressed in the governing equations, as presented in [Figure 6B](#). Real-time simulations of transverse permeability measurements were also conducted to extract the permeability relation using experimental data of the flow rate and injection pressure.

These examples demonstrate how PINNs are transforming composite materials research using more reliable, faster, and data-efficient methods for prediction, design, and analysis. While PINNs offer significant potential in the field of composite materials, conventional PINN models may struggle to fully capture the complex multi-physics and multi-scale issues inherent in composite materials. Obtaining a good balance between physics and data can also be challenging, potentially resulting in slower learning rates or difficulties in convergence. In addition, the training process is sensitive to network hyperparameters and can fall into local minima, and research is ongoing to improve the training performance of PINNs.⁹⁶

To overcome these limitations, it is necessary to enhance model performance by utilizing hybrid models that combine data-driven neural networks with physics-based learning, enabling the simultaneous integration of physical laws and data-based training.^{97,98}

A notable advancement in this field is the development of a transfer learning-based multi-fidelity PINN framework (mfPINN) to mitigate the effects of sparse and noisy sensor data, as well as the limited accuracy of idealized governing equations.⁹⁰ A low-fidelity PINN model is first trained based on the governing physics. Then, the information learned is transferred to a data-driven DNN, which is trained on a smaller set of high-fidelity data, as shown in [Figure 6C](#). The mfPINN framework is used for acoustic source localization in anisotropic composites and is shown to accurately predict the location of defects or signal sources within composite materials. By integrating high-fidelity and low-fidelity data, the mfPINN enhances localization accuracy while preventing data overfitting and reducing the need for expensive high-resolution data, which is often difficult to obtain in practice.

In addition, Hanna *et al.*⁹⁹ used PINNs with CNNs to predict the 2D permeability tensor field of a glass fiber

fabric, including localized variations. Alternatively, PINNs can be combined with numerical solvers to enhance training when simulating multi-scale problems, such as the dual-scale permeability of fibrous reinforcements.¹⁰⁰ Furthermore, applying active learning to efficiently select important training data is expected to provide a more effective learning.¹⁰¹

2.5. Explainable AI (XAI)

XAI is an approach that aims to provide clear and interpretable explanations for the results generated by DL models.^{102,103} Typically, AI functions as a black box, making predictions without offering sufficient insight into the reasoning behind them. However, as illustrated in [Figure 7A](#), the reliability of AI-driven results can be improved by utilizing XAI, which provides a transparent explanation of the decision-making process. This transparency not only enhances the reliability of AI systems but also enables users to better understand and interpret the factors influencing the model's predictions, making AI more accessible in various applications. When using AI for the analysis and design of composite materials, simply obtaining the output values of the results is insufficient. In particular, composite materials exhibit nonlinear properties and are sensitive to numerous factors, requiring careful analysis. While XAI is not a type of DL model, such as DNNs or CNNs, it has been widely used with ML models to predict composite defects, damage, and mechanical properties, explaining the decision-making process and improving the reliability of predictive models.

Several studies have highlighted the potential of XAI in this field.^{32,104-109} Hong *et al.*³² developed a predictive model for the behavior of a composite pressure vessel and utilized XAI to analyze the impact of stacking angle and layer thickness on its performance using permutation feature importance for each design parameter. Daghigh *et al.*¹⁰⁶ developed an XAI-based ML model for predicting defect characteristics (depth, size, and thickness) in composite materials using infrared thermography (IRT) data and evaluated the feature importance of each parameter. Yossef *et al.*¹⁰⁴ predicted the flexural strength of composite laminates using a decision tree-based gradient boosting algorithm as the ML model. They combined the ML model with XAI to analyze how the design parameters influence laminate strength and to provide a visual interpretation of the relationships between these factors ([Figure 7B](#)). Azad and Kim¹⁰⁵ developed an XAI-based model with vision transformers to detect damage in CFRP composites, as shown in [Figure 7C](#). Their approach provided visual insights into areas of delamination, enhancing the damage detection process. Similarly, Song *et al.*¹⁰⁷ applied XAI to textile-reinforced mortar beams to predict the bending

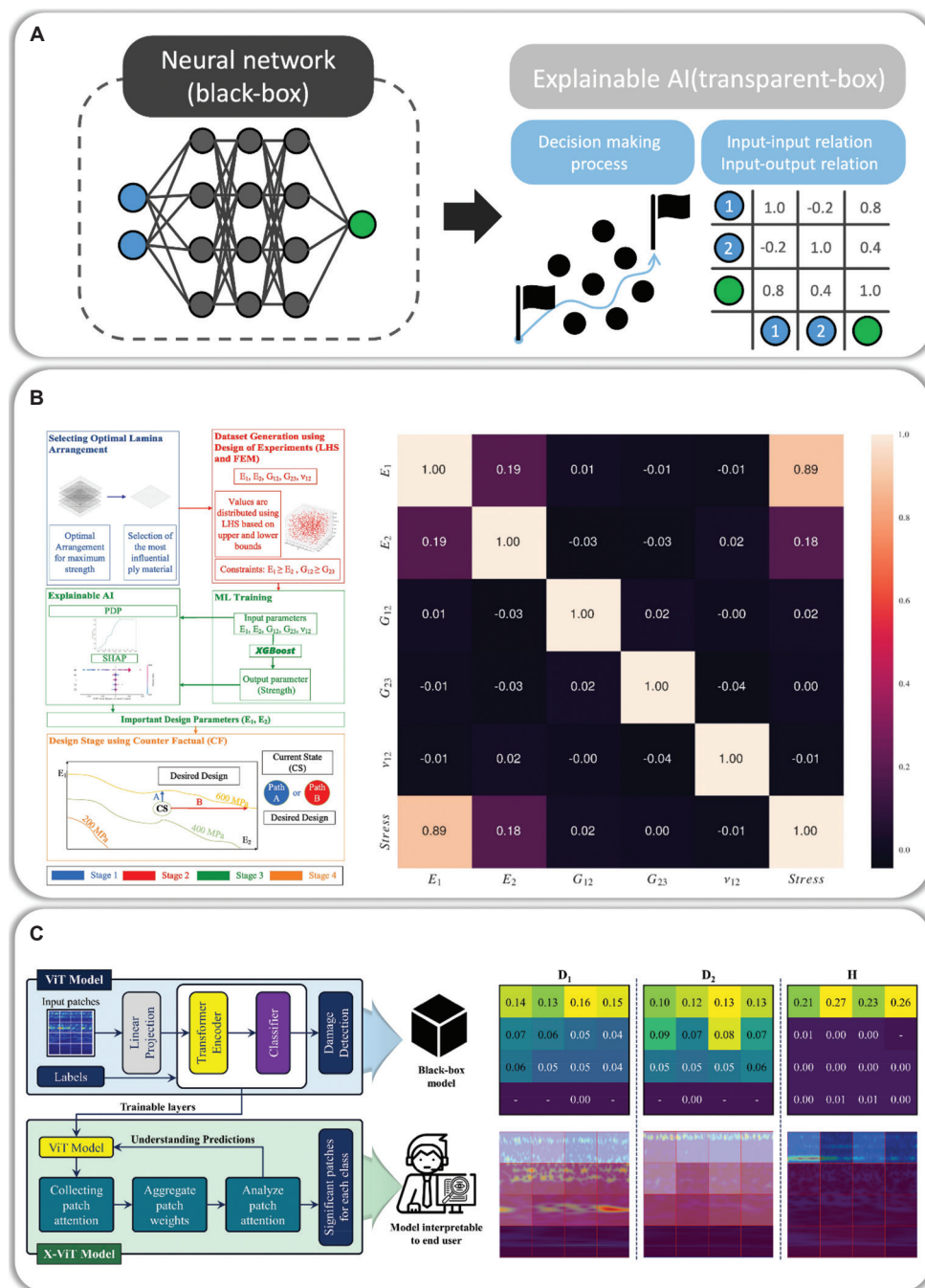


Figure 7. Structure of XAI and research utilizing XAI in the field of composite materials. (A) Structure of XAI; (B) Analysis of the relationships between design parameters of composite laminates and their impact on performance;¹⁰⁴ (C) Methodology and results of utilizing XAI to analyze the delamination mechanisms of composites.¹⁰⁵

Abbreviations: FEM: Finite element method; LHS: Latin hypercube sampling; PDP: Partial dependence plot; SHAP: Shapley additive explanation; ViT: Vision transformer; XAI: Explainable artificial intelligence.

load capacity, revealing the key factors that influence the material's strength, such as the fiber tensile strength and cross-sectional area.

These studies demonstrate the growing role of XAI in composite materials, providing critical insights for

material design, defect detection, and optimization of manufacturing parameters. By combining ML with explainability, XAI is advancing the development of more efficient and transparent processes for the design and manufacture of composite materials.

2.6. Summary of predictive models for composite materials

The applications of predictive ML models in the field of composite materials are summarized in Table 1, along with the advantages and limitations of each type of ML method. The ML approach should be tailored to the target application, as no method is superior to another. The ML framework should be constructed based on the number of variable parameters, the required accuracy of predictions, the type, quantity, and quality of the available data, as well as the knowledge of the governing equations. It is important to understand the characteristics of the problem being modeled to select the most suitable ML method for efficient training and accurate predictions.

3. Generative models for composite materials

Predictive models are designed to predict the output results based on the given input data, whereas generative

models learn from existing unlabeled data to generate new data. In other words, generative models can create entirely new images, texts, designs, and structures, making them particularly valuable for various applications, including data augmentation and innovative design exploration.^{111,112} One of the most well-known examples of generative models is ChatGPT, which demonstrates the potential of this technology in natural language generation. In the field of composite materials, obtaining experimental and simulation data often demands considerable time and cost. Furthermore, the vast range of material combinations and configurations leads to diverse shapes, properties, and characteristics, making the potential applications of generative models even more promising.

3.1. Variational autoencoders (VAEs)

VAEs are the most common types of generative models designed to generate data in a latent space.^{113,114} As depicted in Figure 8A, VAEs primarily consist of an encoder and a decoder, where the encoder maps input data to a latent

Table 1. Applications, advantages, and limitations of predictive models for composite materials

ML method	Applications	Advantages	Limitations
Generic DNNs	-Prediction of nonlinear responses, mechanical properties, structural behaviors of composites, ^{29-31,33,34} and pressure vessel behavior ³²	-Efficient alternative to traditional numerical simulation	-Dependence on large quantities of high-quality data
CNNs	-Analysis of microstructure ^{50,110} -Prediction of stacking angle, ^{45,51} 3D permeability, ⁴⁶ and microstructural property ⁶⁰ -Detection of defect from IR stress measurements, ⁴⁷ damage from lamb wave signals ⁵⁹	-Accurate predictions on image-based data	-Difficulties in collecting sufficient high-quality images. -High pre-processing load
RNNs	-Prediction of nonlinear stress-strain response of composites (elasto-plastic, path-dependent), ⁷⁰ long-term water absorption and swelling, ⁶⁵ dynamic loading behavior in CMCs and concrete granite composites, ^{66,71} shape transformation in 4D printed composites, ⁷³ and fatigue behavior of composites ⁸⁰ -Combination with CNN for spatial-temporal modeling ^{68,83-85}	-Ability to model sequential, time-dependent data, such as stress history or environmental exposure -Support for variable-length data -Use of advanced variants (LSTM, GRU, and Bi-RNN) to enhance prediction stability, memory retention, and directionality	-Need for large training datasets -Limited capability in spatial pattern extraction compared to CNNs -Susceptibility to vanishing/ exploding gradients in generic RNNs
PINNs	-Thermochemical curing process ⁹¹ -Predict composition-property relationships of basalt fibers, ⁹² acoustic source localization in anisotropic composites, ⁹⁰ and property degradation in carbon fiber/epoxy composites ⁹⁵	-No requirement for labelled training data -Physically-consistent predictions beyond the training domain	-Accuracy dependence on the compatibility of governing equations with the modeled process being. -Limitations due to idealized assumptions in governing equations vs. noise and variability in real-world data
XAI	-Analysis of feature importance for composite pressure vessel performance ³² -Prediction of the mechanical strength of the textile-reinforced beam ¹⁰⁷ and defects in composite materials ¹⁰⁶ -Design of FRP laminate ¹⁰⁴ -Detection of visual delamination ¹⁰⁵	-Improved transparency in the decision-making process and prediction reliability -Visualization of influential factors	-Trade-off between explainability and predictive accuracy compared to complex black-box models

Abbreviations: Bi-RNN: Bidirectional recurrent neural network; CMCs: Ceramic matrix composites; CNNs: Convolutional neural network; DNNs: Deep neural networks; FRP: Fiber-reinforced polymer; GRU: Gated recurrent unit; IR: Infrared; LSTM: Long short-term memory; ML: Machine learning; PINNs: Physics-informed neural networks; RNNs: Recurrent neural network; XAI: Explainable artificial intelligence.

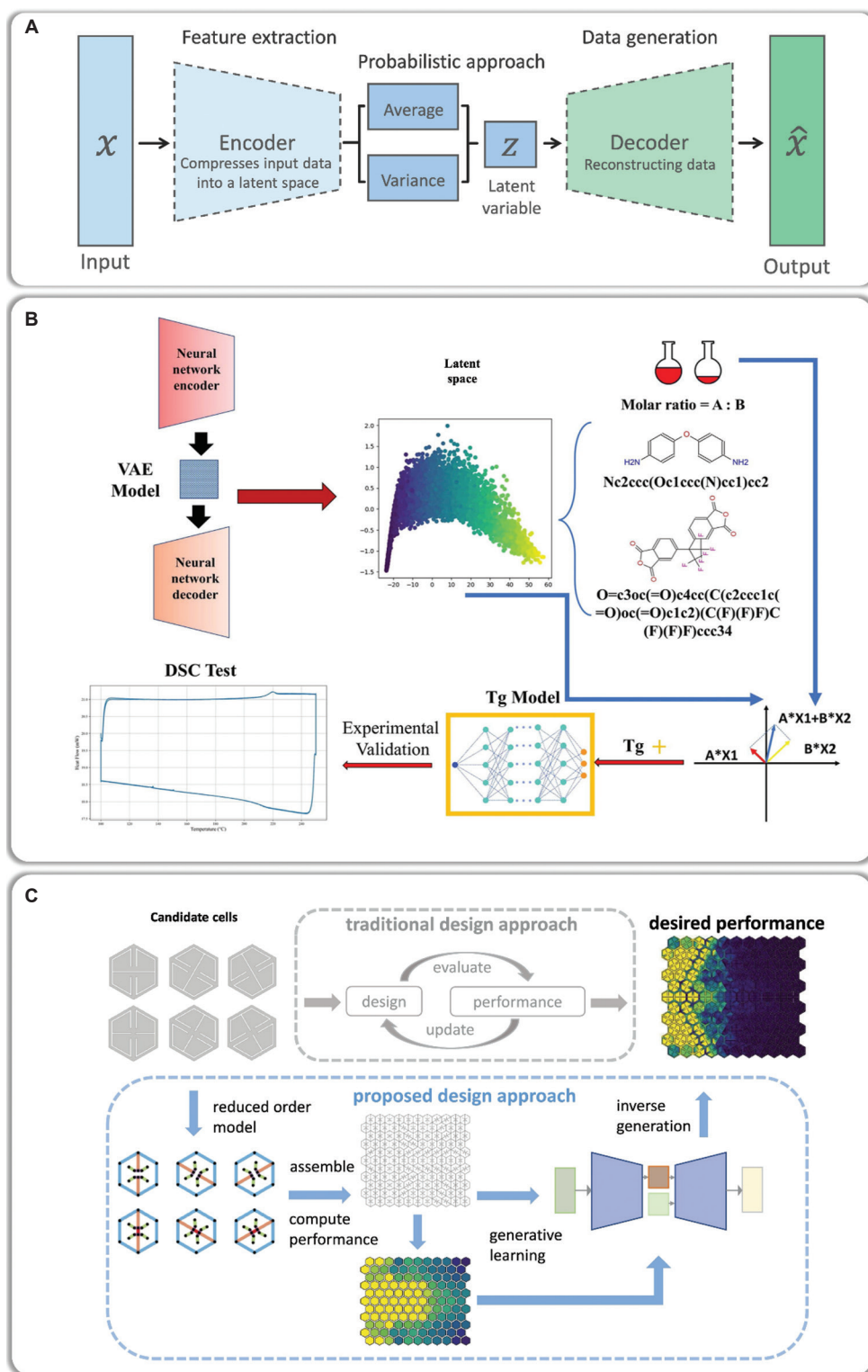


Figure 8. Structure of VAE and research utilizing VAE in the field of composite materials. (A) Structure of VAE; (B) VAE framework for material discovery of SMPs with targeted glass transition temperature.¹¹⁵ Reprinted with permission from Teimouri and Li.¹¹⁵ Copyright © 2024 John Wiley and Sons; (C) VAE framework used for designing unit cells and their arrangements to achieve impact mitigation with desired performance in metamaterials.¹¹⁶ Reprinted with permission from Wang *et al.*¹¹⁶ Copyright © 2024 Elsevier.

Abbreviations: DSC: Dice similarity coefficient; SMPs: Shape memory polymers; VAE: Variational autoencoders.

space, and the decoder reconstructs the original data from the input data. Specifically, to prevent the model from merely replicating the input, VAEs employ a probabilistic approach by encoding the input into the parameters of a Gaussian distribution (i.e., mean and standard deviation), and reconstructing the data by minimizing a loss function composed of a reconstruction loss and a Kullback-Leibler (KL) divergence term. As a result, VAEs are highly useful for generating, transforming, and compressing data, as well as creating new samples.

VAEs can serve as a powerful tool in the field of composite materials to address data scarcity issues and generate new designs.¹¹⁵⁻¹²⁰ For instance, a VAE-based approach was used for generating and optimizing composite layups with specified properties.¹¹⁷ This method allows for increased flexibility in designing complex layup structures and outperforms traditional optimization methods, providing faster results and expanding the design space.

Moreover, as shown in Figure 8B, VAEs were applied to the design and material selection process in the development of thermoset shape memory polymers (SMPs) with high glass transition temperatures. Teimouri and Li¹¹⁵ applied a VAE-based approach coupled with transfer learning to explore the vast chemical design space of SMPs. Their model optimized the glass temperature of SMPs, which was experimentally verified to be highly accurate, thus enhancing the material development process by reducing time and resource consumption.

Furthermore, as presented in Figure 8C, VAEs have also been utilized in the design of metamaterial arrays for impact protection. To address the high computational cost of traditional optimization methods, such as genetic algorithms and Bayesian optimization, Wang *et al.*¹¹⁶ employed VAEs to generate unit cell designs and graded arrays with desired performance. The generated graded metamaterial demonstrated a 97.25% similarity to the target performance and significantly delayed the transmission of impact energy through the material compared to conventional designs.

However, conventional VAEs rely solely on a continuous Gaussian latent space and focus on learning static distributions, which makes it difficult to represent the complex mechanisms of composite materials and limits their ability to predict dynamic changes. Therefore, research is ongoing to apply extended VAE models to resolve these challenges. For instance, the vector quantized-VAE (VQ-VAE) constructs a discrete latent space, allowing the generation of new data through diverse combinations and thus enabling more reliable results. Using VQ-VAE, Wang *et al.*¹¹⁹ predicted the 3D damage field of composite laminates under various low-velocity impact conditions and

demonstrated high performance even with a small dataset. In addition, in a β -VAE, a hyperparameter β is introduced to adjust the weight of the KL divergence term in the standard VAE, thereby promoting statistical independence among latent variables. Jiang *et al.*¹²⁰ predicted the residual stiffness degradation caused by fatigue damage in CMCs with the aid of β -VAE. By combining β -VAE with neural ordinary differential equations, they captured the latent dynamics of fatigue damage progression and reconstructed the full stiffness degradation curves over fatigue cycles. Moreover, their model enabled accurate predictions even under new loading conditions through latent variable interpolation and partial data retraining.

These studies illustrate the versatility of VAEs in enhancing the design and performance of composite materials. By enabling the generation of complex material configurations and reducing the reliance on extensive experimental datasets, VAEs are anticipated to revolutionize the design and optimization of composite structures in various industries, including aerospace, automotive, and civil engineering.

3.2. Generative adversarial networks (GANs)

VAEs are powerful tools for data generation, but the quality of the generated data is relatively low, particularly for applications that require high-resolution images or complex patterns. They also struggle to capture fine details and intricate variations in real-world data, often leading to reconstruction errors, especially with high-dimensional or complex structures. On the other hand, GANs can address these limitations by implicitly estimating the probability distribution, flexibly learning highly complex and nonlinear data distributions in high-dimensional spaces. GANs employ two competing neural networks: a generator, which creates data that mimics real samples, and a discriminator, which distinguishes real data from generated data.¹²¹ The structure of a GAN is depicted in Figure 9A. Through this competitive process, both networks progressively improve, refining the quality of the generated data. Composite material analysis involves capturing details of the intricate microstructures and variations from data consisting of high-resolution images and complex patterns. Consequently, GANs can be a particularly powerful tool in the field of composite materials.

In recent studies, GANs have been used to synthesize realistic 2D microstructures of unidirectional fiber-reinforced composites. Guo *et al.*¹²³ applied a deep convolutional GAN to generate 2D transverse microstructures of fiber reinforced composites. Their approach captured key microstructural features, such

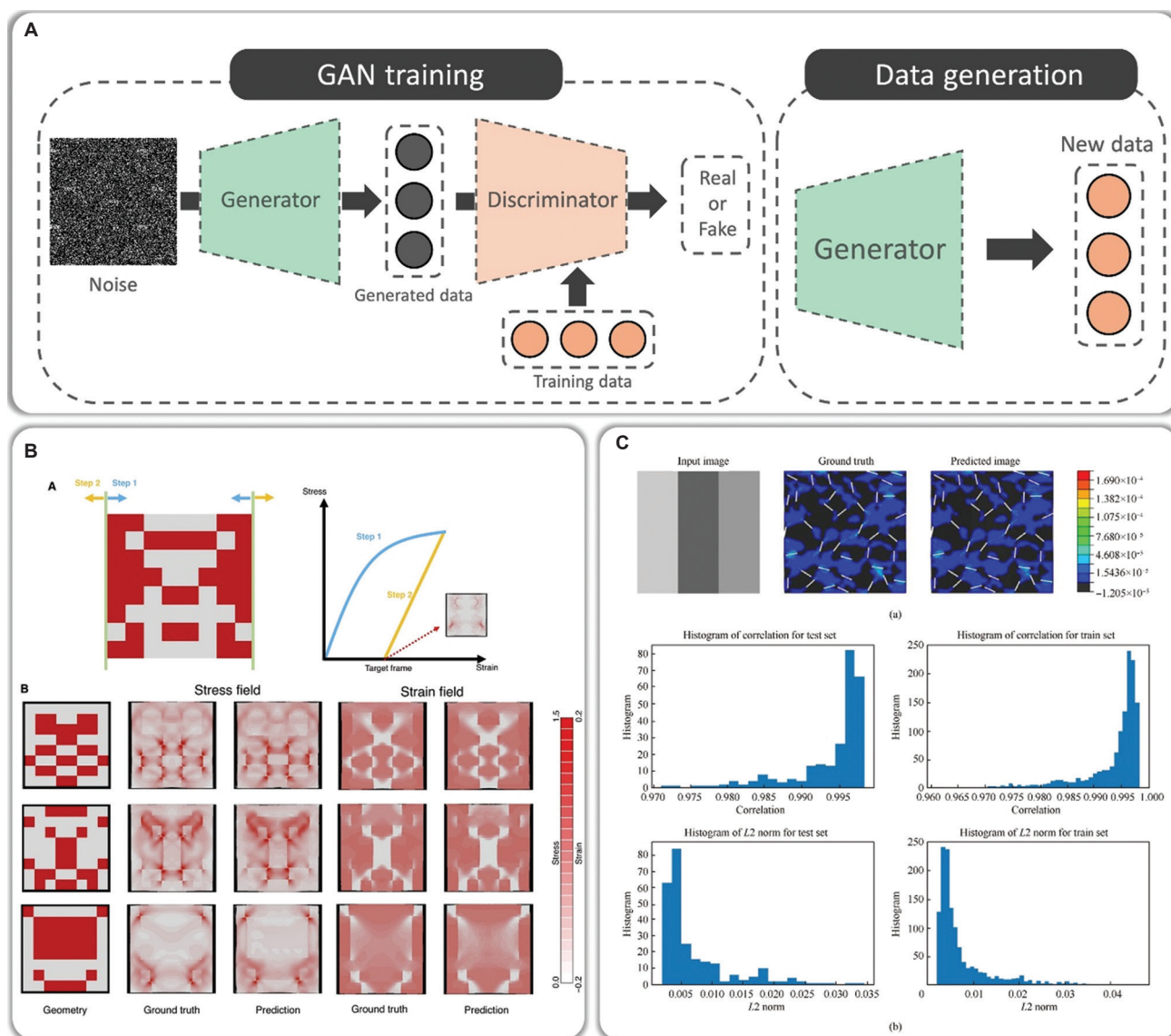


Figure 9. Structure of GAN and research utilizing GAN in the field of composite materials. (A) Structure of GAN; (B) Strain and stress field prediction results using conditional GAN and comparison with FEM (ground truth).¹²² Reprinted with permission from Yang *et al.*¹²² Copyright © 2021 The American Association for the Advancement of Science; (C) Stress field results derived from the microstructure of chopped fiber composites using conditional GAN.¹¹⁰ Abbreviations: FEM: Finite element method; GAN: Generative adversarial network.

as the fiber diameter, fiber volume fraction, fiber spatial distribution, and resin-rich regions, which traditional random microstructure generators struggled to represent. Comparisons of the generated microstructures with real data highlighted the accuracy of GANs in modeling the detailed characteristics of composite structures.

In addition, GANs have been utilized for multi-objective optimization in the design of engineered cementitious composites.¹²⁴ The tensile stress, strain, and cost are optimized simultaneously for varying mixture proportions and fiber types, demonstrating the

potential of GANs for complex multi-variate, multi-objective material design challenges in civil engineering applications.

Another innovative application of GANs is in topology optimization. Li *et al.*¹²⁵ integrated GANs with subset simulation to guide the design of periodic structures with desired bandgap properties. This hybrid approach allows for efficient generation of rare samples in high-dimensional design spaces, facilitating the identification of optimal topologies for composite structures. The method has proven to be effective in the topology optimization of

2D periodic structures, offering new avenues for material design with tailored mechanical properties.

Furthermore, a GAN model, referred to as IRT-GAN, was developed for automated defect detection in composite materials using IRT.¹²⁶ By utilizing simulated large-scale numerical datasets with various defects, IRT-GAN was trained to generate segmentation images of defects automatically. This method demonstrated improved detection performance for both glass fiber- and CFRPs, highlighting the ability of GANs to enhance quality control in composite manufacturing processes.

Conventional GANs generate data solely based on random noise without control over the output. On the other hand, conditional GANs (cGANs) introduce additional conditions to enable the generation of goal-oriented data tailored to specific conditions. Yang *et al.*¹²² utilized cGANs to enhance stress and strain field predictions, as conventional GANs have been shown to generate arbitrary outputs following simple data distributions. As shown in [Figure 9B](#), they accurately predicted both global mechanical properties (e.g., stiffness and resilience) and localized stress concentration phenomena corresponding to specific composite microstructures and loading conditions, achieving computation times of less than one second. Similarly, as shown in [Figure 9C](#), Gupta *et al.*¹¹⁰ developed a CNN-based GAN model to predict principal stress distributions by incorporating factors such as the microstructure of chopped carbon fiber epoxy composites, material properties, and time-dependent loading conditions. These studies present cGAN models as strong candidates for generating and predicting the physical behavior of composites based on their microstructure.

Overall, the integration of GANs into composite material design, optimization, and defect detection presents numerous advantages, including enhanced accuracy in microstructure modeling, multi-objective material optimization, and quality inspection. As these technologies continue to evolve, they hold the potential to revolutionize the development and manufacture of composite materials, leading to higher performance, reduced costs, and improved efficiency in industries such as automotive, aerospace, and civil engineering.

3.3. Other generative models

In addition to VAEs and GANs, diffusion-based deep generative models are being increasingly explored as generative models in the field of composite material research.¹²⁷ Diffusion models consist of a forward phase in which noise is gradually applied to the original image until it resembles Gaussian noise, and the reverse phase in which the model learns the process of progressively

eliminating the noise to obtain the original image, as shown in [Figure 10A](#). This process is based on a Markov chain, where each step refers only to the previous one, enabling stable training through the repeated learning of small changes. As a relatively recent and advanced DL approach, diffusion models demonstrate high performance in generating realistic 2D and 3D composite microstructures by learning from large datasets of actual material structures.^{128,129} As shown in [Figure 10B](#), Lyu and Ren¹²⁸ accurately reconstructed various complex 2D and 3D microstructures of composite materials, such as random textures and chessboard structures, using a diffusion model. The generated images showed distributions highly consistent with the original structures when evaluated using indicators, such as the two-point correlation function, lineal-path function, and Fourier descriptor. Furthermore, conditional generation of 3D structures corresponding to target permeability ranges was also conducted, demonstrating the feasibility of performance-driven inverse material design. As illustrated in [Figure 10C](#), Bastek and Kochmann¹³⁰ proposed a diffusion model-based generative framework to design metamaterial structures that satisfy target stress-strain responses with nonlinear mechanical behavior. They employed a pixel-based 2D microstructural representation as the design parameter, enabling the expression of nonlinear physical phenomena, such as buckling, internal contact, and plastic deformation. After training, the model was evaluated on previously unseen target responses, achieving a normalized root mean square error as low as 1.5%, thereby demonstrating its high accuracy and effectiveness for inverse design applications.

A diffusion-based model is also used by Huang *et al.*¹³¹ for data amplification for non-destructive structural health monitoring of CFRP composite plates using Lamb wave damage signals. It is demonstrated that the diffusion model outperformed VAE and GAN methods in terms of the diversity and quality of the generated samples. With ongoing advancements in ML/DL, diffusion models are poised to play a crucial role in the future of composite material design and optimization.

Normalizing flows (NFs) are a type of generative model that consists of a chain of parameterized invertible mappings to obtain the likelihood of a new sample by transforming the input probability distribution into a well-defined probability distribution, such as the normal distribution. NFs perform sampling, reconstruction, and probability density estimation stably through their invertible structure, which leads to fewer unstable training issues compared to GANs and reduces blurry samples often seen in VAEs. Stochastic inverse design of microstructures for woven CMCs with tailored anisotropic

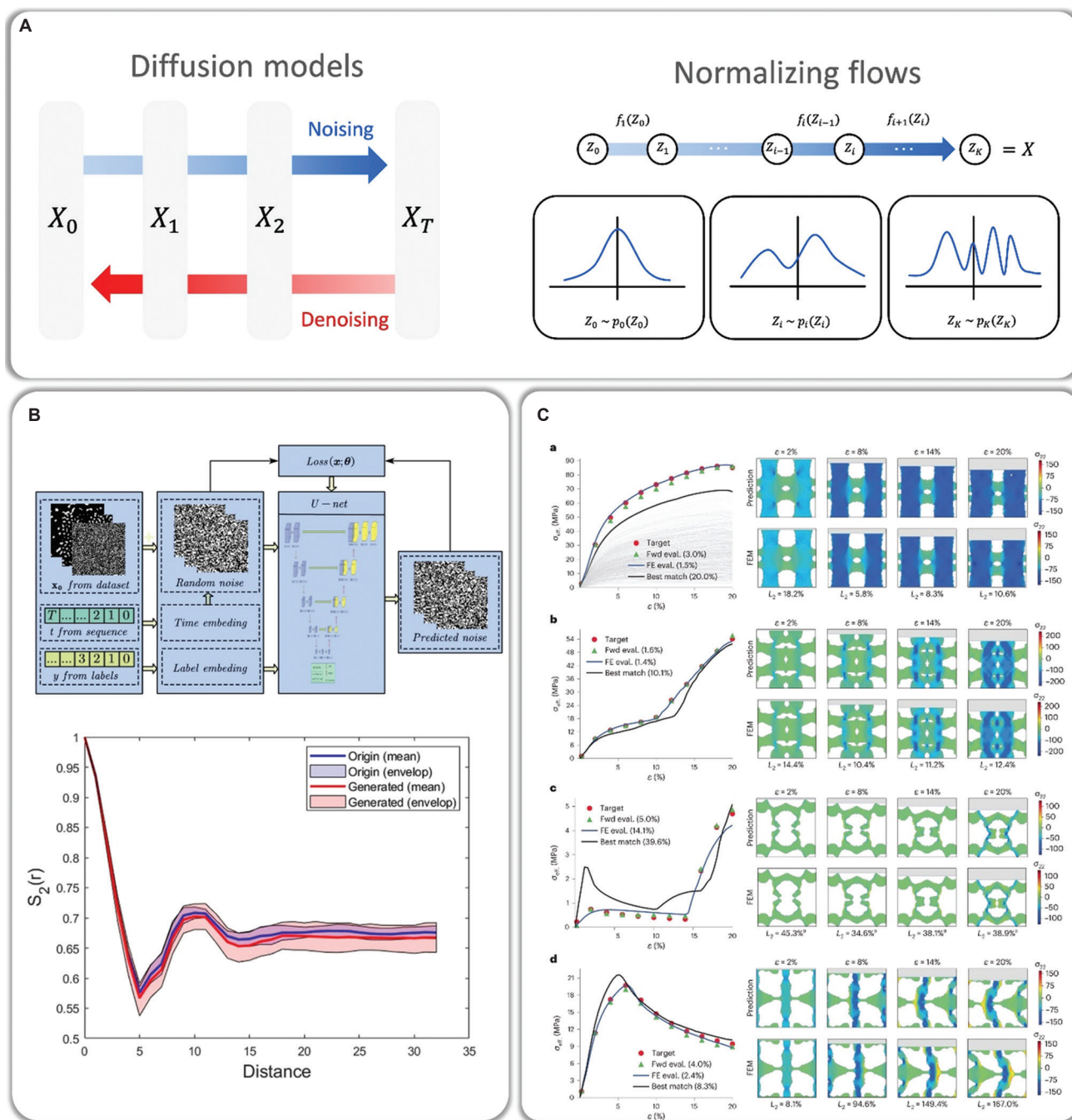


Figure 10. Structures of diffusion models and normalizing flows, as well as research utilizing diffusion models in the field of composite materials. (A) Structure of diffusion models and NFs; (B) The training process of the conditional diffusion model and comparison between the generated microstructures and the original microstructures;¹²⁸ (C) Metamaterial synthesis for four stress-strain responses.¹³⁰

thermal conductivities was conducted through Bayesian inference, combining principal component analysis to reduce dimensionality, a VAE for data compression and to learn the prior distribution, and an NF model to generate new samples.¹³² The framework was able to identify a range of novel microstructures with a target property, rather than a single optimal sample, including samples beyond the

original training set. NFs are also implemented by Mirzaei and Kamrava¹³³ to generate microstructures of porous materials for a given target property from CNN-encoded 3D images via stochastic inverse design. NF models enable the incorporation of the stochastic nature of composite materials, providing a more realistic approach to design and optimization.

3.4. Summary of generative models for composite materials

The applications of generative models in composite materials research are summarized in Table 2, along with the advantages and limitations of each type of ML method.

Although the use of generative models is appealing for discovering new designs and materials, limitations include the difficulty in manufacturing the optimized microstructures, considering the extremely stochastic nature of composite materials. The design process should be constrained by the manufacturability of the generated composite structure, and additive manufacturing and automated technologies could be used in combination with generative models to create more accurately tailored structures.

Moreover, while transformer-based generative models, such as GPT-like architectures, Image GPT, and vision transformer-based diffusion generators,¹³⁴⁻¹³⁶ have not yet been widely applied in composite materials research, their potential in the field is promising. The ability of transformer-based generative models to capture complex patterns and long-range dependencies makes them suitable for applications such as microstructure generation and cross-modal composite design. Future research exploring the adaptation of these foundation models could open new directions for AI-driven composite materials research and further enhance the generative design workflow.

4. Automation models for composite materials

Automation models refer to AI technologies that not only analyze data in real time and make automated decisions but

also actively control, execute, and optimize manufacturing processes. Unlike predictive or generative models that primarily focus on producing outputs from given inputs or generating new data, automation models are characterized by their ability to autonomously manage dynamic workflows through continuous feedback, control strategies, and real-time optimization. This includes decision-making tasks, such as defect detection, process monitoring, and quality control, as well as direct process control, adaptive manufacturing scheduling, robotic motion planning, and real-time process optimization. These models are particularly used in automated manufacturing processes, robotic control systems, and autonomous driving, playing a critical role in improving both efficiency and quality.¹³⁸⁻¹⁴⁰

Composite materials are manufactured through complex processes that often demand significant time and cost. Moreover, manual production can lead to variations in material properties, making defect detection and quality control crucial to maintaining high standards. In addition, the ability to automatically adjust process parameters in real-time is crucial in accommodating the sensitivity of composites to environmental and operational conditions. Therefore, AI automation – encompassing both decision logic and process execution – is emerging as a key technology for enhancing efficiency, consistency, and quality in the production of composite materials. The manufacturing methods and applications utilizing automation models covered in this review are shown in Figure 11A.

4.1. Machine learning/deep learning-driven quality control

Defect detection and quality control are essential to maintain consistent quality and prevent significant

Table 2. Applications, advantages, and limitations of generative models for composite materials

Machine learning method	Applications	Advantages	Limitations
Variational autoencoders	-Composite layup generation and optimization ¹¹⁷ -Shape memory polymer property optimization ¹¹⁵ -Metamaterial design for impact mitigation ¹¹⁶	-Generative and inference models	-Low quality of generated data, especially for high-resolution data or complex patterns
Generative adversarial networks	-Microstructure generation for fiber composites ¹²³ -Engineered cementitious composites: multi-objective material optimization ¹²⁴ -Topology optimization for periodic structures ¹²⁵ -Defect detection in composites ¹²⁶	-High resolution results -Effectiveness for complex multi-modal distributions	-Potential occurrence of mode collapse, resulting in repetitive pattern generations
Diffusion models	-Microstructure generation ¹²⁸ -Data amplification ¹³¹	-High quality and diversity of generated samples	-High Computational demands and need for large training datasets
Normalizing flows	-Microstructure generation with targeted property ^{133,137}	-Likelihood estimation for a given sample	-Complex training processes, sensitivity to model architecture, and scalability challenges

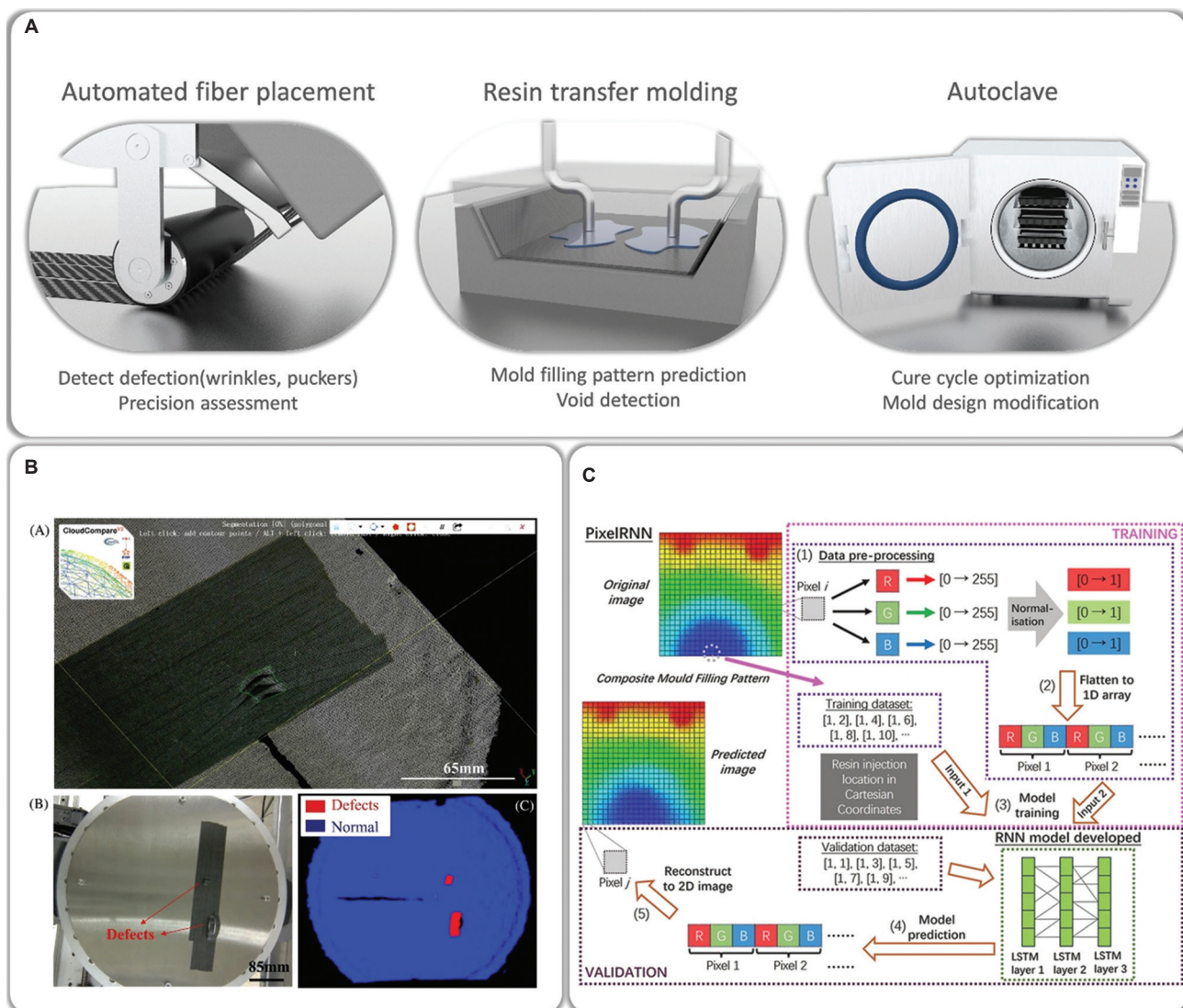


Figure 11. Manufacturing methods and applications utilizing automation models, and research utilizing automation models in the field of composites. (A) Manufacturing methods and applications utilizing automation models; (B) Defect detection results using automation models in the automated fiber placement process.¹⁴¹ Reprinted with permission from Tang *et al.*¹⁴¹ Copyright © 2024 John Wiley and Sons; (C) Study on predicting mold filling patterns in the resin transfer molding process.¹⁴²

Abbreviations: RNN: Recurrent neural network; LSTM: Long short-term memory.

deviations in the properties of composite materials. In particular, the performance of composite materials can be highly sensitive to external environments or specific conditions, making it crucial to analyze and manage these factors precisely. Therefore, the automation of composite material analysis using automation models for quality control is becoming increasingly important.¹⁴¹⁻¹⁴⁵

In quality control applications, CNN-based DL models are extensively employed due to their optimized characteristics for processing image and spatial data through the convolution and pooling of nonlinear high-dimensional feature representations. Machado *et al.*¹⁴³ used

CNNs to develop an automatic system for void content assessment in composite laminates. Voids were detected with high accuracy, and the approach delivered significant improvements over traditional optical microscopy methods by offering faster and more reliable results, even in challenging lighting conditions or with small void sizes. Furthermore, Tang *et al.*¹⁴¹ applied a CNN-based DL model to the automated fiber placement (AFP) process, successfully detecting lay-up defects, such as bridging, wrinkles, and puckers, using 3D scanning data. The model demonstrated high accuracy, particularly for defects with significant height differences compared to the normal

region, as shown in [Figure 11B](#). However, challenges remain in detecting more subtle defects, such as loose tows and twists, where boundary detection becomes more difficult due to minimal height variations or uneven distribution of defects. One of the reasons for this limitation is that CNNs focus on learning local regions, making it difficult to capture global relationships. To address this limitation, many studies have explored the use of other DL models.

For instance, Liu *et al.*¹⁴⁴ integrated a transformer-based neural network with a CNN for automatic delamination detection in composite curved structures. This transformer-based model can learn correlations among elements within the entire image through a self-attention mechanism, enabling the detection of defects with high accuracy by considering patterns and morphological information. Moreover, by utilizing enhanced terahertz time-domain spectroscopy signals for non-destructive testing and imaging of hidden delamination defects, the transformer-based approach demonstrated superior accuracy and generalization performance compared to traditional models, highlighting its potential for real-time defect detection in complex composite structures. This method could be particularly beneficial in industries such as aerospace, where structural integrity is critical. In addition, the potential for ML/DL-driven automation in the quality control of the RTM process was demonstrated by Wang *et al.*¹⁴² The PixelRNN model, an image-based neural network architecture, was used to predict mold filling patterns with high accuracy given the resin injection location, as shown in [Figure 11C](#). This model was particularly effective in handling nonlinear filling patterns and significantly reduced computational costs compared to traditional physics-based simulations. This highlights the increasing role of ML/DL in process monitoring and automatic detection of dry spots in resin impregnation processes.

In addition, as described in Sections 3.2 and 3.3, generative models, such as GANs,¹²⁶ VAEs,¹¹⁸ and diffusion models,¹³¹ were also used to detect and classify defects in composite materials. In contrast to the methods of defect detection, which require data from both normal and defective samples, Szarski and Chauhan¹⁴⁶ developed a model based on NFs to obtain the image likelihood of a new sample using the knowledge learned from input images of only normal samples. Considering the rarity and variety of defects, collecting training data is expensive and time-consuming, and supervised learning proves to be difficult. Instead of detecting the presence of defects, the model determines whether the sample is different from a set of normal samples, without requiring any data from defective samples. Furthermore, Zhang *et al.*¹¹⁸ focused

on the use of a VAE combined with Bayesian neural networks (BNN) to quantify damage in composite plates. This semi-supervised learning model helps with structural health monitoring by effectively handling the uncertainty and measurement errors prevalent in damage detection. The VAE-BNN model achieved high accuracy for several damage types, such as cracks and delamination, offering improved robustness against noise compared to traditional methods.

These studies exemplify the growing impact of automation models in improving quality control in composite material manufacturing. The presence of defects, such as voids or wrinkles, can significantly compromise the mechanical properties of composite parts. By automating defect detection and enhancing defect characterization, ML/DL technologies are transforming the production of composite materials, ensuring better quality, reducing production times, and achieving cost savings in the long run. Moreover, the integration of ML/DL allows for continuous monitoring and real-time adjustments to further enhance the precision and efficiency of the production process.

4.2. Machine learning/deep learning-driven process automation

The production of composite materials has traditionally relied on the expertise of skilled professionals. While the work of these skilled experts remains an effective method for producing composite materials, the manufacturing process is highly dependent on external environments and conditions and susceptible to human error, requiring advanced technical skills and labor-intensive efforts. In addition, some processes may generate harmful chemicals that might have negative impacts on the health of workers.

Due to these limitations, there has been an increasing interest in automation in composite material manufacturing. However, simple mechanical automation is insufficient considering the complex shapes and variable manufacturing conditions associated with composite materials. In other words, advanced AI-based automation technology with the flexibility to adapt to diverse shapes and complex conditions is essential for composite material manufacturing.

These innovations are particularly important in manufacturing processes, such as AFP, RTM, and composite curing, where high precision and efficiency are critical.¹²⁷⁻¹²⁹ A hybrid framework combining spatial-temporal analysis, thermography, and ML algorithms was recently developed for process monitoring and defect detection in AFP.¹⁴⁷ In this framework, an extensive thermal image database was used to train the model, achieving an impressive accuracy

in defect detection. The approach demonstrates a good balance between real-time performance and accuracy, optimizing the AFP part quality and enhancing the overall process efficiency. In addition, the integration of decision support systems in AFP would be beneficial, as these systems assist in defect detection, segmentation, and precision assessment, further streamlining the process.

In terms of process optimization, a theory-guided probabilistic ML (TGML) approach has been proposed for minimizing process-induced deformations (PIDs) in composite materials.¹⁴⁸ This method provides a reliable prediction model for optimizing key process parameters, such as layup design and curing cycles, using minimal experimental data. By utilizing TGML, the study identified an optimal layup configuration and curing cycle, achieving significant reductions in PIDs and production costs. The study demonstrates how ML can be applied to optimize complex manufacturing processes without the need for extensive experimental trials.

In the domain of composite curing, deep reinforcement learning has been employed to optimize temperature profiles and tooling during the curing process.^{76,127,130} Würth *et al.*⁹¹ demonstrated the application of PINNs for cost optimization of the thermochemical curing process of a composite plate. The use of PINNs resulted in speed improvements by over 500 times compared with conventional finite element simulations, demonstrating their potential to significantly reduce simulation times and enhance process efficiency. Similarly, Humfeld *et al.*¹⁴⁹ optimized the air temperature profile for composite curing subject to process constraints, such as cure duration and maximum part and air temperatures, using a PINN framework. Their multiple neural network framework consisted of four neural networks, each representing a different process variable, and a series of transfer learning stages with increasing complexity to ensure training convergence. Through reinforcement learning-based process control, Szarski and Chauhan¹⁴⁶ improved the air

temperature profile for CFRP curing, resulting in a 40% reduction in curing time compared to traditional methods. Furthermore, the study employed Bayesian optimization to adjust the mold thickness based on the geometry of the CFRP part, improving heat transfer and preventing local overheating. This approach demonstrates the potential of reinforcement learning as autonomous AI optimizes both process time and energy consumption, thereby significantly enhancing the efficiency of the composite curing process.

4.3. Summary of automation models for composite materials

These advancements highlight the growing role of AI in automating and optimizing the composite manufacturing process. To date, only a limited number of studies have applied autonomous AI in composite materials research. With continuous improvements in process monitoring, modeling, and optimization, ML/DL-driven approaches are paving the way for more efficient, reliable, and cost-effective production of composite materials. Table 3 provides a summary of the applications of automation models in the field of composite materials, with the advantages and limitations.

5. Conclusion and future perspectives

In this paper, the innovative potential of AI in the design, manufacturing, and analysis of composite materials is investigated through a systematic study of predictive, generative, and automation models.

Predictive models have shown exceptional performance in predicting the physical properties of composite materials, microstructure analysis, and design parameter estimation, utilizing techniques including DNNs, CNNs, transfer learning, and PINNs. Generative models play a crucial role in the design and optimization of new materials, microstructure design, and the discovery of novel materials, offering innovative solutions in the field of composite materials based on various techniques,

Table 3. Applications, advantages, and limitations of automation models for composite materials

Applications	Advantages	Limitations
Void detection in laminates using CNN, ¹⁴³ defect detection in AFP using CNN, ¹⁴¹ delamination characterization using transformer, ¹⁴⁴ RTM mold filling prediction using PixelRNN, ¹⁴² and defect detection using GAN/diffusion/NF ^{126,131,146}	-High defect detection accuracy -Automation of the detection process -Improved production quality and reduced time/cost	-Difficulty in detecting subtle defects -Challenges in data acquisition -Requirement for integration with manufacturing processes
AFP process monitoring using ML and thermal imaging, ¹⁴⁷ curing process optimization with TGML, ¹⁴⁸ curing profile optimization with reinforcement learning, ¹⁴⁶ and composite curing optimization using multi-stage PINN ¹⁴⁹	-Optimization of manufacturing efficiency and precision -Reduction of human error -Lower production costs	-Complexity of system integration -Sensitivity to external environment variations

Abbreviations: AFP: Automated fiber placement; CNN: Convolutional neural network; GAN: Generative adversarial network; ML: Machine learning; NF: Normalizing flow; PINN: Physics-informed neural network; RNN: Recurrent neural network; RTM: Resin transfer modeling; TGML: Theory-guided probabilistic machine learning.

such as VAEs and GANs. Automation models, which make automated decisions during the manufacturing process through real-time data analysis, prediction, and optimization, play a significant role in improving efficiency and quality, and are expected to make key contributions to enable widespread adoption and popularization of composite materials. Through various research examples, the paper confirms that ML provides a new paradigm for research in composite materials.

Despite these advancements, several critical challenges remain. Data scarcity continues to limit ML performance, highlighting the need for data-efficient approaches, such as transfer learning, few-shot learning, and the development of large-scale open datasets. Enhancing data accessibility and promoting widespread data-sharing within the research community will be highly beneficial for accelerating ML-driven advancements in composite materials research. Moreover, to maximize the practical utilization of ML, combining and applying multiple ML methodologies appropriately becomes increasingly important. Generalization issues, particularly the difficulty of applying trained models to new materials or conditions, can be addressed by embedding physics-based knowledge into ML frameworks through hybrid modeling and domain adaptation techniques. In addition, rather than relying on blind data accumulation, more efficient learning through intentional human-driven data curation is expected to enhance ML performance. Challenges regarding training instability and lack of interpretability require further research on regularization and the adoption of XAI approaches. Furthermore, the real-world deployment of AI models faces significant challenges related to robustness, latency, and safety. These challenges can be mitigated through advances in edge computing, digital twin frameworks, real-time AI inference technologies, and specialized ML hardware, such as neural processing units. Finally, integrating emerging technologies, such as quantum computing, may further enhance the scalability, reliability, and industrial adoption of AI-driven solutions in the research and manufacturing of composite materials.

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Conflict of interest

Seong Su Kim is an Editorial Board Member of this journal but was not in any way involved in the editorial and peer-review process conducted for this paper, directly or indirectly. Separately, other authors declared that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Availability of data

No datasets were generated or analyzed during the current study.

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