물리적 특징을 활용한 CNN 기반 단방향 섬유 강화 복합재의 기계적 특성 예측

CNN-based Prediction of Mechanical Properties in Unidirectional Fiber-Reinforced Composites using Physics-Guided Features

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1. Introduction

Composite materials are widely used in aerospace and automotive industries due to their high strength-to-weight ratio and durability. However, their heterogeneous microstructure and complex failure behavior make it challenging to predict mechanical properties accurately [1]. While Finite Element Method (FEM) simulations offer reliable results, they are computationally expensive for large-scale studies. Experimental methods, though accurate, are also costly and time-consuming.

To accelerate the design process, Convolutional Neural Networks (CNNs) have emerged as efficient alternatives for predicting material properties from microstructure images [2, 3]. Yet, many existing models are limited to small fiber volume fraction ranges, omit failure-based features, and show limited generalization to unseen microstructures.

This study introduces a hybrid approach that integrates Representative Volume Element (RVE) generation, FEM simulations, and CNN-based learning. Scalar indicators derived from classical failure criteria - such as Tsai–Wu, Hashin, and Puck - are used as augmentation features and combined with microstructure images to train CNNs for predicting the Young's modulus, ultimate tensile strength, and toughness across a broad range of fiber volume fractions [1, 4, 5]. Accuracy and generalization are further improved by integrating attention modules - specifically Squeeze-and-Excitation (SE) blocks and Convolutional Block Attention Modules (CBAM) - as well as applying transfer learning [6, 7, 8].
The key contributions of this study are:

- Broader Applicability – Expands the fiber volume fraction range from 5% to 60%, enabling broader material design.
- Enhanced Feature Integration – Adds failure criteria as augmentation features.
- Improved Feature Extraction – Employs attention mechanisms to highlight critical microstructural features.
- Better Generalization – Applies transfer learning to increase robustness and reduce data dependency.
- Extended Property Prediction – Predicts not only stiffness and strength but also toughness.

2. Computational Framework for Microstructure-Based Property Prediction

2.1. RVE Generation and Finite Element Simulation

To model unidirectional composites under plane strain conditions, two-dimensional RVEs were generated with randomly placed circular carbon fibers using random Random Sequential Expansion (RSE) and Random Fiber Removal (RFR) algorithms [9, 10]. The fibers were embedded in an epoxy matrix, and periodic boundary conditions were applied to ensure representative behavior. Transverse tensile loading under displacement control was simulated for each RVE. Fiber volume fractions ranged from 5% to 60% in 5% increments, resulting in a dataset of 2400 simulations.

2.2. Feature Extraction and Augmentation

To improve predictive accuracy and incorporate failure-relevant information, scalar stress-based features were extracted from each FEM simulation. These include the von Mises stress σ_v, maximum principal stress σ_i, and failure indices based on classical composite criteria: Tsai–Wu T, Hashin H_T & H_C, and Puck P [1, 4, 5]. Each criterion yields a single scalar value per RVE. These features were appended to the CNN input, allowing the network to account not only for geometric fiber patterns but also for physically meaningful indicators of mechanical failure.

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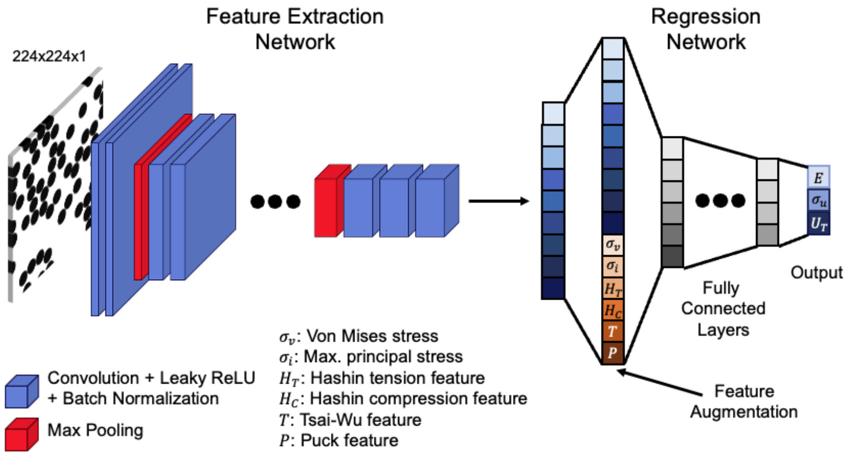

Figure 1: Examplary representation of the proposed CNN architecture.

2.3. *Convolutional Neural Network Architecture*

The CNN input consists of grayscale images representing fiber distributions, augmented with scalar features extracted from FEM simulations. The network architecture comprises multiple convolutional layers with Leaky ReLU activations, batch normalization, and max pooling for feature extraction, followed by fully connected regression layers that predict Young's modulus E, ultimate tensile strength σ_u, and toughness U_T. To enhance spatial focus and reduce noise, attention mechanisms such as SE and CBAM were integrated [6, 7]. The influence of these mechanisms and various augmentation feature sets was systematically assessed to evaluate their impact on model performance.

3. Conclusions

The proposed framework combines FEM simulations with deep learning to predict key mechanical properties of unidirectional fiber-reinforced composites. Among various model configurations, attention mechanisms - particularly CBAM - proved most effective in improving prediction accuracy. In contrast, physics-based augmentation features such as Tsai–Wu, Hashin, and Puck offered only marginal benefits. The best performance was achieved using a ResNet-50 architecture with transfer learning, highlighting the strength of advanced feature extraction over purely physics-informed inputs.

These findings demonstrate the potential of combining physics and data-driven methods for efficient, accurate composite property prediction across a broad range of microstructural configurations. Future work will focus on incorporating nonlinear fracture behavior through phase-field modeling, as well as refining CNN architectures and input representations to further improve generalization and interpretability.

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Acronyms

FEM	Finite Element Method
RVE	Representative Volume Element
CNN	Convolutional Neural Network
RSE	Random Sequential Expansion
RFR	Random Fiber Removal
SE	Squeeze-and-Excitation
CBAM	Convolutional Block Attention Modules