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

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Attention mechanisms and transfer learning led to strong performance gains with minimal implementation effort, outperforming physics-based augmentation features in this study.

Abstract

This study presents a hybrid framework that combines FEM simulations and Convolutional Neural Networks (CNNs) to predict the mechanical properties of unidirectional fiber-reinforced composites. Physics-guided scalar features were used alongside microstructure images to train the models. While these features offered minor improvements, attention mechanisms and transfer learning led to better results with minimal implementation effort.

Introduction

Predicting the mechanical behavior of composites is challenging due to their heterogeneous microstructure and complex failure behavior.

- FEM simulations provide accurate results but are computationally expensive.
- CNNs offer a data-driven alternative by learning structure-property relations from fiber distributions.

This study evaluates the effectiveness of physics-based augmentation features compared to modern deep learning strategies.

Methods

Two-dimensional Representative Volume Elements (RVEs) were created using Random Sequential Expansion (RSE) and Random Fiber Removal (RFR) algorithms to model unidirectional fiber-reinforced composites with fiber volume fractions from 5% to 60%. FEM simulations under transverse tension produced 2400 samples, combining linear elastic modeling with cohesive zone modeling for fiber-matrix interfaces.

The following scalar variables were extracted from the FEM results:

- Von Mises Stress
- Max. Principal Stress
- Tsai-Wu, Hashin, and Puck criteria

These features were combined with binary microstructure images to train CNNs. We tested:

- A baseline CNN (images only)
- Models with Augmentation Features (AFs)
- Attention-enhanced CNNs (SE, CBAM)
- Transfer Learning using ResNet-50

Conclusion

Attention mechanisms – especially CBAM – and transfer learning significantly improved model accuracy. In contrast, the augmentation features had only a limited effect. ResNet-50 performed best overall, followed closely by the CBAM-based model – underscoring the power of modern deep learning approaches in this context.

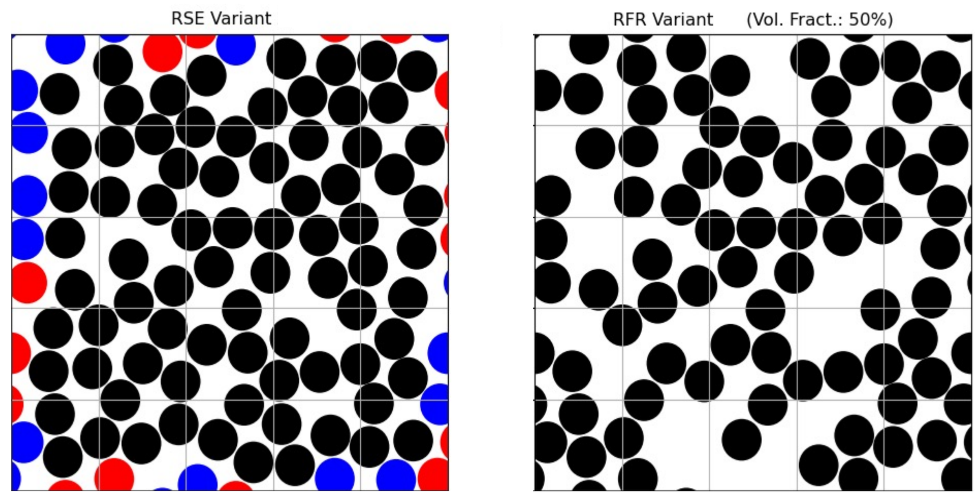
Outlook

- Integration of Phase-Field Modeling (PFM) to capture matrix failure
- Further refinement of the CNN architecture
- Exploration of additional augmentation features and identification of the most effective ones

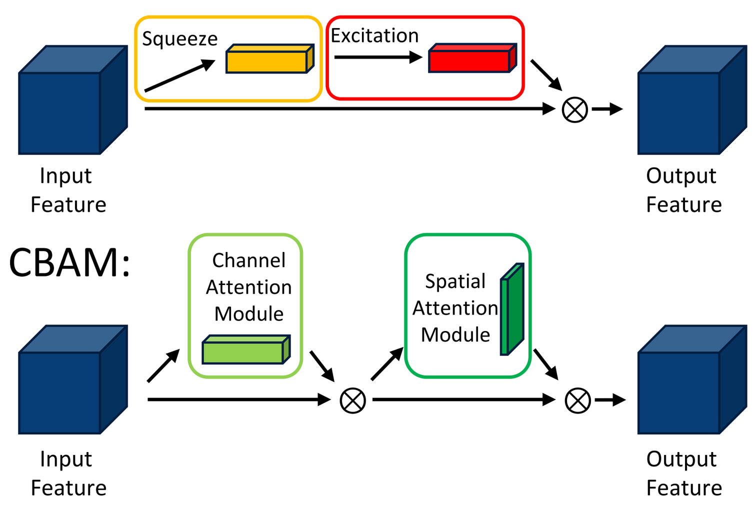
Scan for:

lab website, poster & extended abstract.

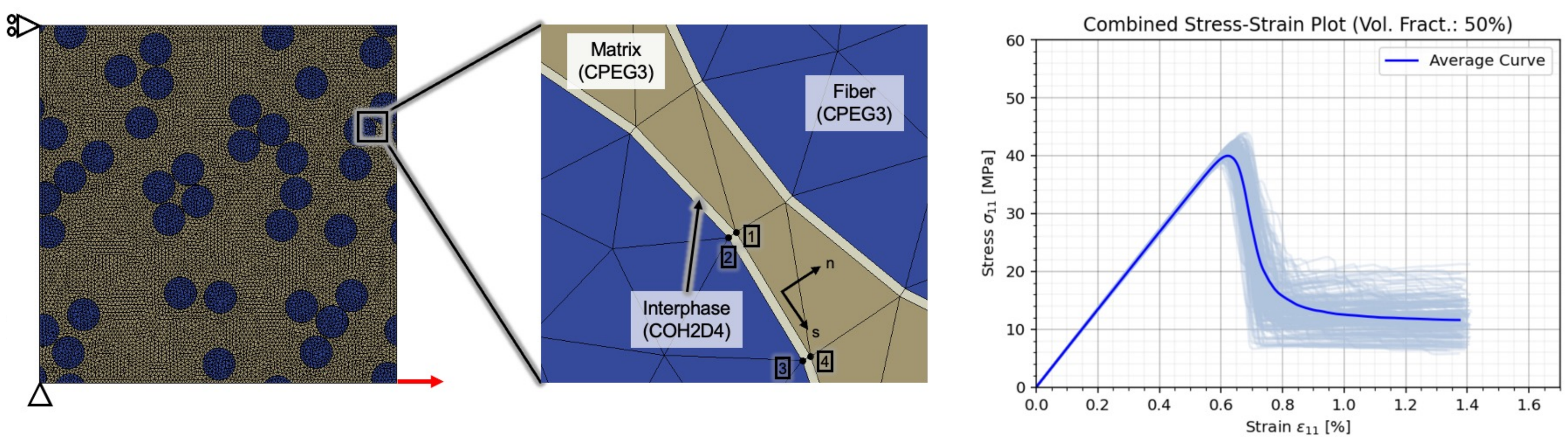
RSE & RFR Algorithms



Attention Mechanisms



FEM Simulation Setup & Stress-Strain Curves



Augmentation Features

Tsai-Wu: $T = F_1\sigma_{11} + F_2\sigma_{22} + 2F_{12}\sigma_{11}\sigma_{22} + F_{11}\sigma_{11}^2 + F_{22}\sigma_{22}^2 + F_{66}\tau_{12}^2$

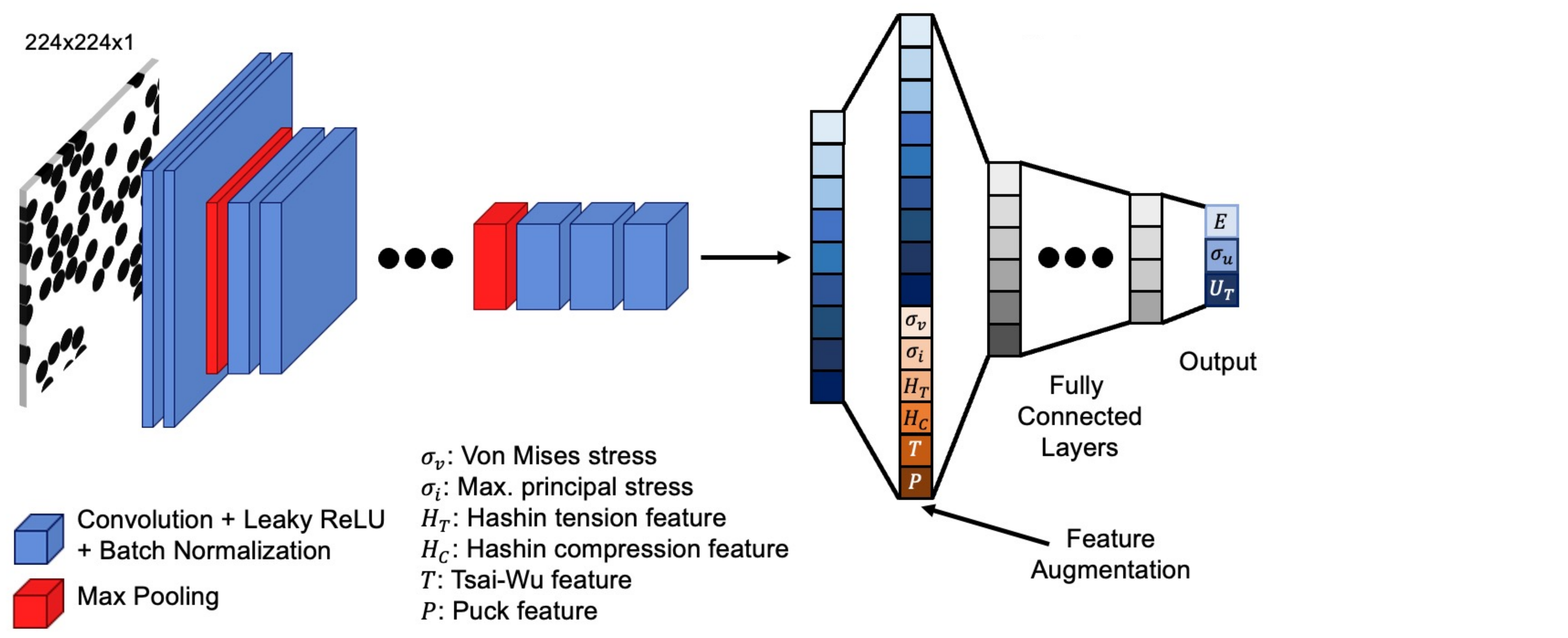
$$F_{11} = F_{22} = \frac{1}{\sigma_u^M \sigma_c^M}; F_1 = F_2 = \frac{1}{\sigma_u^M} - \frac{1}{\sigma_c^M}; F_{66} = \frac{1}{(\tau^M)^2}\ ;\ F_{12} = \alpha\sqrt{F_{11}F_{22}}$$

Hashin (Tension): $H_T = \dfrac{(\sigma_{11}+\sigma_{22})^2}{(\sigma_u^M)^2} + \dfrac{(\tau_{12}^2 - \sigma_{11}\sigma_{22})}{(\tau^M)^2}$

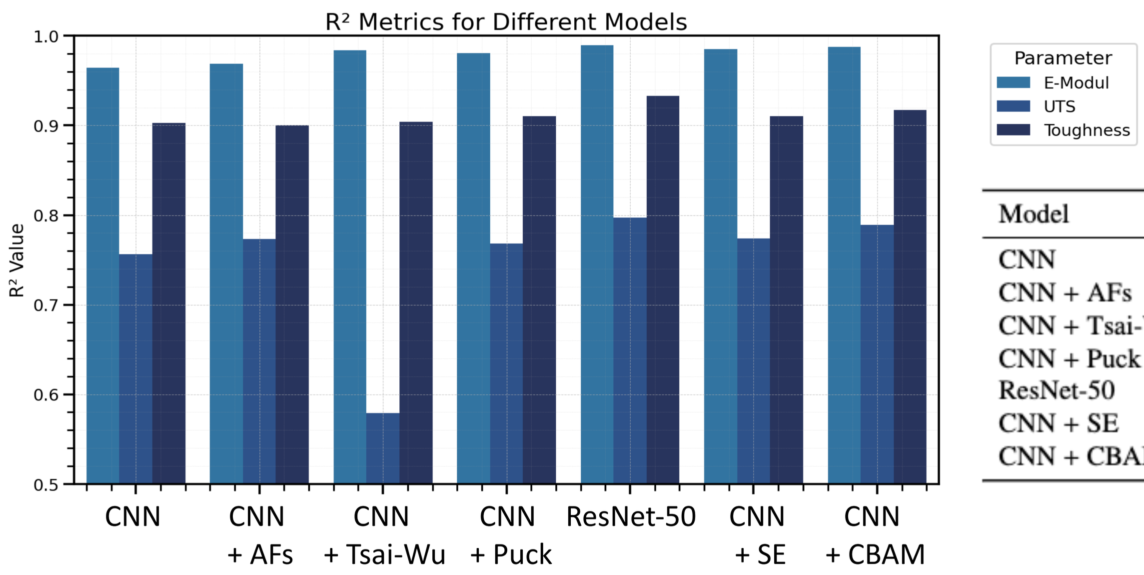
Hashin (Compression): $H_C = \dfrac{(\sigma_{11}+\sigma_{22})}{\sigma_c^M}\left[\left(\dfrac{\sigma_c^M}{2\tau^M}\right)^2 - 1\right] + \dfrac{(\sigma_{11}+\sigma_{22})^2}{4(\tau^M)^2} + \dfrac{(\tau_{12}^2 - \sigma_{11}\sigma_{22})}{(\tau^M)^2}$

Puck (Mode A): $P = \sqrt{\left(1 - p\dfrac{\sigma_u^M}{\tau^M}\right)^2 \left(\dfrac{\sigma_{11}}{\sigma_u^M}\right)^2} + p\dfrac{\sigma_{11}}{\tau^M}$

CNN Architecture



Prediction Results



Model	E-Modulus, E	UTS, σ_u	Toughness, U_T
CNN	0.965	0.757	0.903
CNN + AFs	0.969 (+0.4%)	0.773 (+2.1%)	0.900 (-0.3%)
CNN + Tsai-Wu	0.984 (+2.0%)	0.579 (-23.5%)	0.904 (+0.1%)
CNN + Puck	0.981 (+1.7%)	0.768 (+1.5%)	0.910 (+0.8%)
ResNet-50	0.990 (+2.6%)	0.797 (+5.3%)	0.933 (+3.3%)
CNN + SE	0.985 (+2.1%)	0.774 (+2.2%)	0.911 (+0.9%)
CNN + CBAM	0.988 (+2.4%)	0.789 (+4.2%)	0.917 (+1.6%)

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