

Physics-Informed Machine Learning for Predicting Buckling Performance and Damage Evolution in Graphene Reinforced Basalt/Epoxy Composites

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Research Article

Keywords: Progressive damage modeling, Basalt composites, Micromechanics, FEM

Posted Date: July 10th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10113791/v1>

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Additional Declarations:

No competing interests reported.

Table 5 is not available with this version

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Abstract

Basalt fiber-reinforced polymer composites are attractive for lightweight structural applications due to their high specific strength, thermal stability, and environmental sustainability. Their performance is limited by weak fiber–matrix interfaces, premature damage initiation, and insufficient compressive stability. This study presents an integrated experimental–computational framework to improve the structural performance of basalt/epoxy composites through dual-phase reduced graphene oxide (rGO) functionalization. Basalt fibers were coated with rGO using electrophoretic deposition, while rGO was simultaneously incorporated into the epoxy matrix through a hybrid ultrasonication–high-shear dispersion process. Mechanical characterization demonstrated that dual-phase functionalization significantly enhanced tensile, compressive, interlaminar shear, and fracture properties by improving interfacial bonding and matrix stiffness. The experimentally optimized composite was incorporated into a multiscale modeling framework in which representative volume element (RVE)-based homogenization was used to determine effective orthotropic properties for nonlinear finite element analysis. Progressive damage behavior under compressive loading was evaluated using Hashin failure criteria coupled with continuum damage mechanics. A comprehensive dataset comprising 12,852 laminate configurations was generated by varying geometric parameters and stacking sequences and was subsequently used to develop machine-learning surrogate models for prediction of critical buckling loads. An ensemble model combining linear regression and support vector regression achieved a coefficient of determination of 0.973. SHAP-based interpretation identified laminate length and width as the dominant parameters governing buckling resistance. Progressive damage analysis further revealed that dual-phase rGO functionalization delays damage initiation and promotes stable load redistribution. The proposed framework provides an efficient pathway for the design and optimization of lightweight, damage-tolerant composite structures.

Keywords: Progressive damage modeling; Basalt composites; Micromechanics; FEM

Introduction

Fiber-reinforced composites are becoming very important in engineering since they are light, strong, and can be used in many various ways. Basalt fiber-reinforced composites (BFRCs) are becoming more popular as a green replacement for glass and carbon fiber composites. To make basalt fibers, volcanic rocks that are already in the ground are melted and pushed through a mold. This makes them affordable, safe, and easy to recycle [1–3]. They are stable at high temperatures, have great tensile strength, and don't break down or corrode [4–7]. These features, together with the fact that basalt fibers are naturally abundant and can be created in a method that is environment friendly, have made them potential for structural usage in civil engineering parts, aerospace interiors, automotive panels, and nautical constructions [8–10]. Basalt fibers are more stable at high temperatures, have a greater specific modulus, and are less likely to break down when they come into contact with chemicals than glass fibers [11, 12].

Basalt fiber composites have these advantages, but they also have certain disadvantages that make them less able to handle heavy loads in advanced structural uses. Weak fiber–matrix adhesion, sensitivity to interfacial flaws, and limited toughness are three things that let damage start and spread more quickly when mechanical stress is applied [13, 14]. Moreover, the compressive strength of basalt composites is frequently influenced by micro-buckling and fiber instability rather than the inherent yielding of the material. These issues make the structure less efficient, cause it to delaminate, and make it less able to handle damage than synthetic composites such as carbon/epoxy systems [15–18]. Researchers are looking for different ways to make BFRCs stronger at the interface, make the matrix tougher, and make them less likely to get damaged over time so that they may be used in different applications.

Functionalizing nanomaterials is now a good technique to solve these challenges. Researchers have looked into graphene and its derivatives a lot since they are exceedingly stiff, have a high aspect ratio, and have a unique layered structure [19, 20]. The rGO has a large surface area and several functional groups on its surface, which makes it easier for it to interact with polymer matrices and fiber surfaces [21]. Adding rGO to polymer matrices has been demonstrated to make them stiffer, stronger in tension, and harder against breaking by making it simpler for loads to travel through them and encouraging cracks to bend and fibers to bridge [22]. Coating the surface of reinforcement fibers with rGO considerably increases interfacial adhesion, reduces interfacial voids, and makes the surface rougher, which helps the fibers lock into the matrix better [23]. Also, rGO acts as a barrier layer, stopping moisture from moving through it and making fiber-reinforced composites last longer [24]. Many research have looked at how to add rGO to composites, but most of them have only looked at rGO-reinforced matrices or rGO-coated fibers [25–27]. For basalt composites with high aspect ratio fibers, compressive performance is frequently limited by fiber kinking, localized delamination, and the advancement of progressive deterioration [28]. Matrix reinforcement has been shown to improve bulk stiffness and resistance to cracks, while fiber coating mainly improves bonding between fibers and protects against moisture. To our knowledge, the synergistic approach of dual rGO functionalization, which incorporates rGO in the matrix and coating fibers with rGO, has not been previously explored in BFRC systems. This novel method is expected to simultaneously resolve the inadequate fiber–matrix interfacial bonding, premature matrix fracture, improve load-bearing capacity, fracture resistance, and overall damage tolerance in basalt fiber-reinforced composites.

Despite significant progress in graphene-modified composites, existing studies predominantly focus on either matrix-level nano modification or fiber surface functionalization in isolation, with limited efforts toward integrating both approaches within a unified structural performance framework. Furthermore, prior investigations largely treat experimental characterization, numerical simulation, and data-driven optimization as independent processes, lacking a physically consistent linkage across scales. In particular, the translation of nanoscale interfacial enhancements into macroscale structural stability, especially under nonlinear buckling and progressive damage conditions remains insufficiently understood. To address these gaps, the present study develops four distinct basalt/epoxy composite systems with different rGO functionalization strategies, including matrix modification, fiber surface coating, and their combined dual-phase approach. Fiber surface modification was achieved via electrophoretic deposition (EPD), producing a uniform and continuous rGO coating on basalt fibers, while matrix modification was performed using a hybrid ultrasonication high-shear dispersion technique to ensure homogeneous nanoparticle distribution and prevent agglomeration. Comprehensive mechanical characterization, including tensile, compressive, flexural, interlaminar shear strength, and fracture toughness testing, was conducted to evaluate the

influence of each functionalization strategy, with results demonstrating that dual-phase rGO functionalization provides the most significant enhancement in load-bearing capacity through improved interfacial adhesion and increased matrix stiffness. Building upon this experimentally identified optimal configuration, a micromechanics-informed, experimentally anchored multiscale framework is proposed, wherein RVE-based homogenization is used to extract orthotropic properties reflecting nanoscale reinforcement effects, followed by nonlinear finite element modeling incorporating progressive damage via Hashin criteria to capture buckling behavior and failure evolution. A large parametric dataset was subsequently generated by varying geometric parameters and stacking sequences, enabling the development of a machine learning-based surrogate model using an ensemble of linear regression and support vector regression for rapid prediction and optimization of buckling performance. Unlike conventional approaches where machine learning is applied as a standalone predictive tool, the present work employs physics-informed machine learning trained on high-fidelity FEM data, enabling both accurate prediction and mechanistic interpretability through SHAP-based feature attribution. Progressive damage analysis further elucidates the role of dual-phase functionalization in delaying damage initiation and controlling failure propagation. This integrated methodology establishes a direct and traceable link between material modification, structural response, and data-driven optimization, and to the best of the authors' knowledge, represents the first comprehensive experimental computational investigation demonstrating the role of dual-phase rGO functionalization in enhancing nonlinear buckling response and progressive damage behavior of basalt fiber-reinforced composites, thereby providing a robust pathway for the multiscale design of damage-tolerant, high-performance composite structures.

Experimental

Materials

Premium Coatings and Chemical in Chennai, India supplied epoxy-curing agent, 1041 Phenalkamine hardener, and bisphenol-A-based unmodified liquid epoxy resin. AdNano, Chennai, India, supplied reduced graphene oxide (rGO) with over 95% carbon. Chennai-based Funique Composites Private Limited sold basalt textiles.

Fabrication

Dual functionalization of reduced graphene oxide (rGO) was accomplished by applying a coating of rGO onto basalt fibers using electrophoretic deposition (EPD) and integrating rGO into the epoxy matrix through a hybrid ultra-sonication and high-shear dispersion technique. Composite were produced utilizing the VARTM technique, succeeded by regulated curing and post-curing to guarantee consistent resin penetration and reduced void content. The rGO content utilized for epoxy modification and fiber surface coating was determined based on a previous optimization study conducted by the authors [23, 26], in which various weight fractions of rGO were thoroughly assessed. The chosen concentrations (0.75 weight percent for epoxy modification and 0.3 weight percent for fiber coating) demonstrated the optimum mechanical performance due to their uniform dispersion, enhanced interfacial bonding, and reduced agglomeration effects. The ideal values were used in this work to guarantee effective reinforcing and precisely evaluate the impact of dual-phase rGO functionalization on the low-velocity impact behavior of the composites. Figure 1 depicts a schematic of the production process, whereas the Supplementary Data (S1) provides specific experimental procedures,

including sample preparation, dispersion techniques, and EPD parameters. The manufactured samples and composite configurations are displayed in Figure F1 and Table 1, respectively. For low-velocity impact testing, specimens measuring 100 mm × 150 mm × 3 mm were built in accordance with ASTM D7136/D7136M [31]. Composites were made using unidirectional plain-weave basalt fabrics with a symmetric stacking pattern of [90/45/0/0/45/90]. Prior to testing, the specimen edges were polished to reduce edge damage, and the average value for analysis was determined by measuring the thickness at three different sites using a digital micrometer.

Table1: Sample details.

Sample Code	Sample Description	Epoxy Matrix Condition	Basalt Fiber Condition
BEC	Basalt fiber reinforced epoxy composite	Neat epoxy (no modification)	Untreated basalt fibers
BREC	Basalt fiber composite with rGO-modified epoxy	Epoxy reinforced with 0.75 wt.% rGO	Untreated basalt fibers
CBEC	Composite with rGO-coated basalt fibers in epoxy	Neat epoxy (no modification)	Basalt fibers coated with 0.3 wt.% rGO
CBREC	Hybrid composite with both rGO-modified epoxy and rGO-coated fibers	Epoxy reinforced with 0.75 wt.% rGO	Basalt fibers coated with 0.3 wt.% rGO

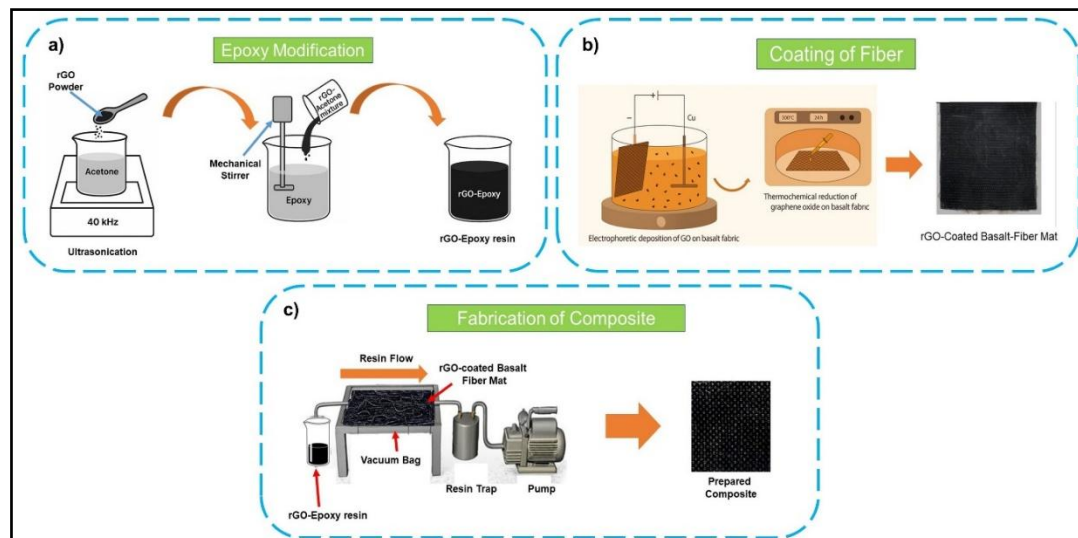


Figure 1. Fabrication Process (a) Coating of Fiber (b) Epoxy Modification (c) Fabrication of Composite.

Mechanical Characterization

Tensile strength –

Tensile tests were performed utilizing a Zwick Roell-Z010 universal testing equipment, which had a 20 kN load cell and a clip-on extensometer with a 10% strain capability. Specimens were manufactured in accordance with ASTM D638 (Type I geometry), assuring uniform gauge length and cross-sectional dimensions to reduce variability. All tests were conducted at a uniform crosshead velocity of 3 mm/min under displacement-controlled loading conditions. Wedge grips were employed to avert slippage, and alignment was meticulously verified before testing to prevent bending loads.

Compression strength –

Compression tests were conducted utilizing the Zwick Roell-Z010 universal testing equipment, adhering to ASTM D6641 standards [31]. Specimens were constructed with suitable end-tab designs to provide consistent load distribution and to reduce the risk of premature failure caused by stress concentrations. A compression fixture was employed to avert global buckling during testing and to guarantee that failure resulted from material behavior rather than structural instability. Experiments were performed using displacement-controlled loads, and seven specimens were assessed for each composite arrangement.

Interlaminar Shear Strength –

The interlaminar shear strength (ILSS) was assessed by a short-beam shear test following ASTM D2344-84, utilizing a Shimadzu AGS-10 kN universal testing equipment. Specimens were evaluated using a span-to-thickness ratio of 4:1 (span length of 12 mm), and loading was administered at a crosshead velocity of 1 mm/min. Seven specimens were evaluated for each arrangement, and average values were documented to guarantee statistical reliability.

Fracture Toughness –

The composite material's fracture toughness was measured using a Mode-I stress SENB specimen [33]. ASTM D5045 was followed to make the specimen. Computerized universal testing equipment tested the item at 1 mm/min crosshead velocity. Determining the fracture load with a load displacement diagram helped reveal crack propagation. Mode-I critical fracture was calculated using Equation (1). The material's fracture toughness was calculated by averaging seven specimens of each composition.

$$K_{IC} = \frac{P}{B \times W^{0.5}} f\left(\frac{a}{W}\right) \quad (1)$$

Where K_{IC} is fracture where P , B , W and a are the peak load, specimen thickness, specimen width and crack length, respectively.

$$G_{IC} = \frac{K_{IC}^2}{E} \quad (2)$$

Where E is effective modulus

FEA and Machine Learning Coupled Method

Representative volume element (RVE) –

Representative volume element (RVE) modeling was employed to determine the effective mechanical properties of the composites through micromechanics-based homogenization [32]. The RVE captured the geometry and spatial distribution of constituent phases, including fiber morphology and matrix–fiber interactions. It has been used to study nanocomposites of polymers reinforced with iron oxide and carbon fibers, as well as hybrid composites with natural fibers and CNT nanoparticles [33]. Homogenization was performed in ANSYS 2024 R1 by applying appropriate boundary conditions (periodic or kinematic with prescribed macroscopic strains) to compute the effective stiffness matrix. A hexagonal RVE of size $500 \times 500 \times 500 \mu\text{m}$ with a mesh size of $3 \mu\text{m}$ was used, incorporating material properties listed in Table 2 [26]. Mesh and RVE convergence were verified, with variations in homogenized moduli maintained below 3%. The resulting orthotropic elastic constants were subsequently used as input for laminate-level finite element simulations. Figure 2 illustrates the developed RVE and the corresponding orthotropic properties for the CBREC composite.

Table 2: Properties of epoxy and fiber.

Properties	Epoxy	Basalt Fiber	rGO Modified Epoxy	rGO Coated Basalt Fiber
Density (g/cm^3)	1.17	2.59	1.16	2.6
Young's Modulus (GPa)	1.41	87.12	1.83	106
Bulk Modulus (GPa)	1.55	68.08	2.03	85.34
Shear Modulus (GPa)	5.18	33.81	6.77	40.97
Poisson's Ratio	0.35	0.287	0.351	0.293

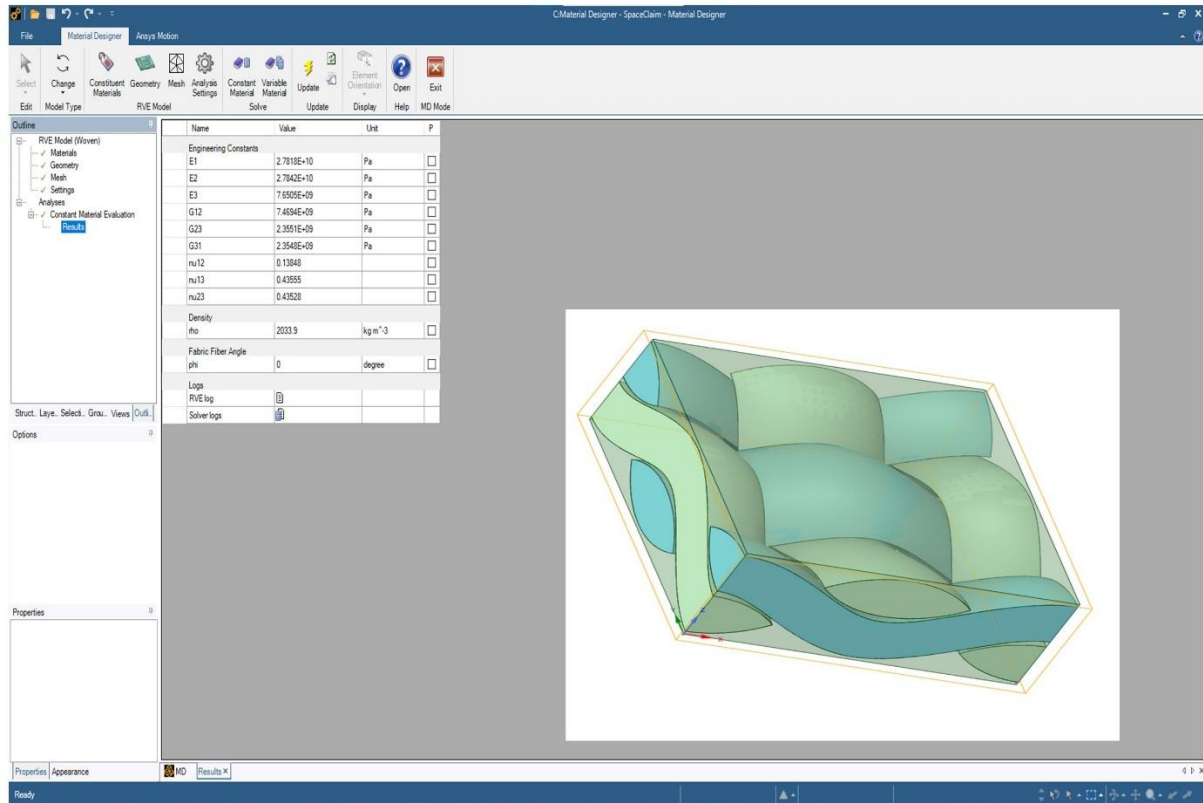


Figure 2: Developed RVE and orthotropic elastic property of CBREC composite.

FEM Model –

The critical buckling load was used as the primary metric to evaluate compressive stability of the composites. An integrated framework combining nonlinear finite element analysis and machine learning was developed to predict and optimize the buckling behavior of dual-phase rGO-functionalized basalt/epoxy laminates (Figure 3). Orthotropic properties obtained from RVE homogenization in ANSYS 2024 R1 were assigned to laminate models. A parametric dataset was generated by varying geometry and stacking sequences, followed by nonlinear buckling analysis to capture realistic structural response beyond linear eigenvalue predictions. Laminates were modeled using SHELL181 elements in ANSYS ACP Pre [34], incorporating geometric nonlinearity and tracking the nonlinear load multiplier as the stability criterion. Mesh convergence was ensured with variations below 3%, and a mesh size of 0.5 mm was adopted. All simulations included geometric imperfections. A compressive load of 1000 N was applied, and the critical buckling load was obtained from the corresponding load factor. Progressive damage was incorporated using Hashin failure criteria to capture damage initiation and evolution under compression. The generated dataset was subsequently used to train ensemble machine learning models for rapid prediction of buckling load, and optimized configurations were further analyzed to evaluate damage progression.

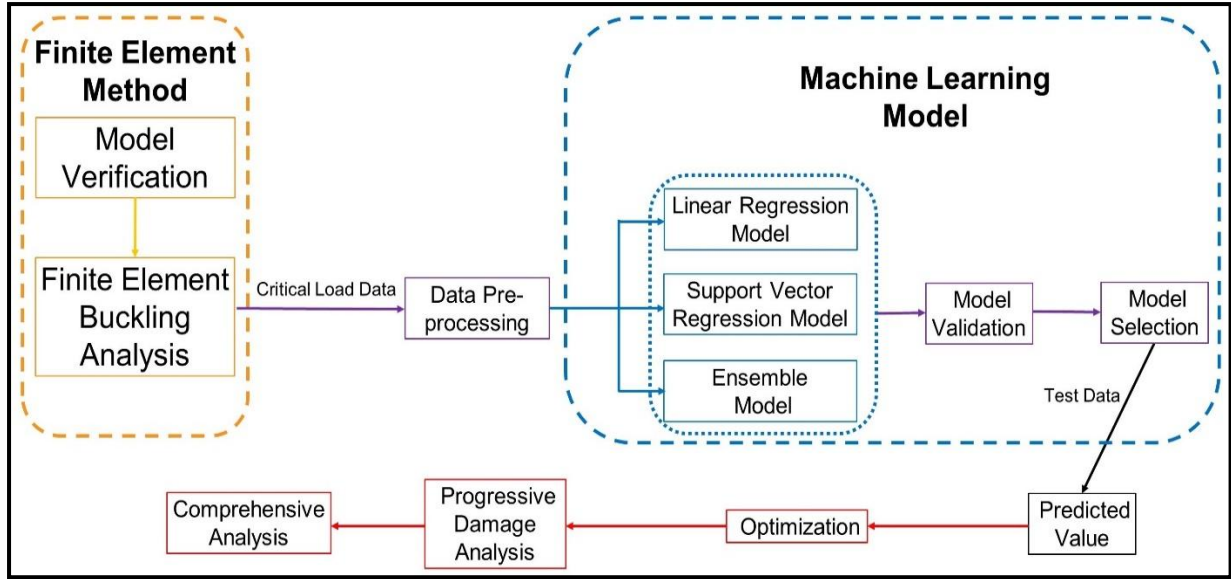


Figure 3: Schematic representation of framework.

Progressive Damage Model

Progressive damage evolution was modeled using Hashin failure criteria within a continuum damage mechanics (CDM) framework. Intralaminar failure modes, including fiber tension/compression and matrix tension/compression—were considered. Damage initiation activated scalar damage variables ($0 \leq d \leq 1$), enabling stiffness degradation and simulation of post-failure behavior, thereby capturing progressive damage evolution in the composite [35]. This made it possible to model post-failure behavior and capture fiber-matrix nonlinear stiffness decrease and damage interaction. This framework accurately illustrated the initiation and subsequent deterioration of buckling-induced damage in CBREC laminates.

In the numerical analysis, damage to the fiber reinforced composites specimen is determined by any or a combination of the following failure mechanisms.

- Matrix failure (in both tension and compression)
- Fiber failure (in both tension and compression)

Tensile fiber mode, $\sigma_{11} > 0$

$$\left(\frac{\sigma_{11}}{X_T}\right)^2 + \left(\frac{\tau_{12}}{S}\right)^2 \geq 1 \quad (1)$$

Compressive fiber mode, $\sigma_{11} < 0$

$$\left(\frac{\sigma_{11}}{X_C}\right)^2 \geq 1 \quad (2)$$

Tensile matrix mode, $\sigma_{22} > 0$

$$\left(\frac{\sigma_{22}}{Y_T}\right)^2 + \left(\frac{\tau_{12}}{S}\right)^2 \geq 1 \quad (3)$$

Compressive matrix mode, $\sigma_{22} < 0$

$$\left(\frac{\sigma_{22}}{Y_C}\right) \left[\left(\frac{Y_C}{2S}\right)^2 - 1 \right] + \left(\frac{\sigma_{22}}{2S}\right)^2 + \left(\frac{\tau_{12}}{S}\right)^2 \geq 1 \quad (4)$$

σ_{11}, σ_{22} : Normal stresses in fiber and transverse directions.

τ_{12} : In-plane shear stress.

X_T, X_C : Fiber tensile and compressive strengths.

Y_T, Y_C : Matrix tensile and compressive strengths.

(S): Shear strength.

A scalar damage variable (d) will be added, with values between 0 (not harmed) and 1 (completely failed). As damage gets worse, the rigidity of the material will slowly go down. Energy-based criteria will be used to model post-failure behavior so that the mesh stays objective.

Determination of Material Parameters for Progressive Damage and Cohesive Zone Modeling

The material parameters used in the Hashin progressive damage model was obtained from the comprehensive mechanical and fracture characterization of the same hierarchical rGO-modified basalt/epoxy composite system reported in our previous study [41]. Orthotropic elastic constants, tensile and compressive strengths, and shear properties were determined experimentally through tensile, compression, and shear characterization, while fracture energy parameters were derived from measured energy absorption and fracture toughness responses. The resulting constitutive parameters, summarized in Table 3 and Table 4, were subsequently used as inputs for the Hashin damage initiation and damage evolution. The detailed experimental procedures, parameter derivation methodology, and constitutive framework have been reported in this work [36]. The experimentally determined strength parameters adopted for the Hashin damage initiation criteria are presented in Table 5. These values define the onset of fiber and matrix failure under tensile, compressive, and shear loading conditions and were obtained from the mechanical characterization of the developed laminates [36].

Table 3: Experimentally determined strength parameters used in the Hashin damage model [36].

Parameter	BEC	BREC	CBEC	CBREC
Longitudinal tensile strength, (X_T) (MPa)	380	425	470	515
Longitudinal compressive strength, (X_C) (MPa)	200	235	275	320
Transverse tensile strength, (Y_T) (MPa)	132	155	172	192
Transverse compressive strength, (Y_C) (MPa)	98	112	128	145
In-plane shear strength, (S_{12}) (MPa)	48	58	70	82
Out-of-plane shear strength, ($S_{13}=S_{23}$) (MPa)	32	43	55	68

The intralaminar fracture energy parameters used for damage evolution are summarized in Table 4. These values were derived from experimentally measured energy absorption and fracture toughness responses and were used to govern stiffness degradation and progressive damage propagation after failure initiation [36].

Table 4: Experimentally derived intralaminar fracture energy parameters used for damage evolution [36].

Fracture energy parameter	BEC	BREC	CBEC	CBREC
Fiber tensile fracture energy, (N/mm)	0.45	0.52	0.58	0.62
Fiber compressive fracture energy, (N/mm)	0.30	0.34	0.38	0.42
Matrix tensile fracture energy, (N/mm)	0.48	0.62	0.74	0.90
Matrix compressive fracture energy, (N/mm)	0.32	0.35	0.37	0.41

Rationale for Machine Learning Integration

The incorporation of machine learning (ML) into the current framework is driven by the computational intricacy linked to nonlinear finite element simulations of composite structures. Although high-fidelity finite element methods yield precise predictions of buckling behavior and progressive damage, they are computationally intensive when investigating extensive design spaces with numerous geometry and stacking sequence variables. This study's parametric FEM analysis produced 12,852 design configurations, rendering iterative evaluation for optimization impracticable. To mitigate this limitation, machine learning models were created as surrogate models trained on finite element method-generated data, facilitating swift prediction of critical buckling stresses without necessitating repetitive numerical simulations. The ML technique, in contrast to traditional lookup tables, captures intricate nonlinear correlations between input parameters (geometry, stacking sequence) and structural

reaction, facilitating continuous prediction throughout the design space instead of discrete interpolation. Moreover, employing an ensemble learning approach that integrates linear regression (LR) and support vector regression (SVR) allows the model to concurrently identify global linear patterns and localized nonlinear interactions characteristic of composite buckling behavior. The integration of SHAP (SHapley Additive exPlanations) analysis enhances model interpretability, enabling the quantitative evaluation of each design variable's impact. This converts the ML model from a solely predictive instrument into a design-assistive framework that can detect predominant structural parameters and facilitate optimization. This work highlights that ML does not supplant physics-based modeling; instead, it serves as a computationally efficient augmentation to FEM, enabling swift design exploration, sensitivity analysis, and robustness assessment. This hybrid FEM–ML methodology markedly improves the scalability and practical utility of the suggested framework for the design of real-world composite structures.

Machine Learning Model

To examine data-driven predictions of laminate buckling reaction, this work developed three separate machine learning models to estimate the critical buckling strength of materials with diverse microstructures and components. This research investigated how well the linear regression (LR) model, the ensemble model, and the Support Vector Regression (SVR) model could make predictions. These models were chosen to show two different ways of learning: parametric and non-parametric. We also tested how well they could predict outcomes when used together in an ensemble. The dataset was made using parametric finite element analysis (FEA) with a Python ANSYS interface. We split the dataset so that 80% was for training and 20% was for testing. GridSearchCV was used to optimize the hyperparameters, and the coefficient of determination (R^2) and root mean square error (RMSE) were the main metrics used to do so.

To assess the efficacy of the models, it is necessary to incorporate all definitions of error.

$$MAE = \frac{1}{n} \sum_{i=1}^n |\theta_i - \hat{\theta}_i| \quad (5)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{\theta_i - \hat{\theta}_i}{\theta_i} \right| \times 100\% \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\theta_i - \hat{\theta}_i)^2} \quad (7)$$

$$R^2 = \frac{[\sum_{i=1}^n (\theta_i - \theta_i^{mean})(\hat{\theta}_i - \hat{\theta}_i^{mean})]^2}{[\sum_{i=1}^n (\theta_i - \theta_i^{mean}) \sum_{i=1}^n (\hat{\theta}_i - \hat{\theta}_i^{mean})]} \quad (8)$$

This made it possible to optimize CBREC composites under compressive loads.

Linear Regression (LR) –

Linear Regression (LR) was used as a baseline model to find worldwide linear connections between the critical buckling load and geometric parameters (length, breadth, and thickness), and stacking sequence descriptors. Its simplicity and interpretability establish it as a common reference model, however it may be constrained in its ability to capture the nonlinearity intrinsic to composite postbuckling behavior.

Linear regression is a basic machine learning technique that works on the idea that inputs and outputs have a linear relationship. This can be written mathematically as follows [37]:

$$y_p(X) = w_o + \sum_{i=1}^m X_i w_i \quad (9)$$

Where w_o is a constant; m is the number of input parameters; w_i is the regression coefficient; and X_i and y_p are the input variables and predicted outputs, respectively. The elements in the matrix X represent the length, width and thickness of the composite, and the stacking sequence corresponds to the LR model's prediction of the critical buckling strength.

To find the regression coefficient w , the error between the true value and the predicted output value has to be as small as possible. This was done using [38]:

$$w = \operatorname{argmin} \left[\sum_{j=1}^M (y_i - f(x_j))^2 \right] \quad (10)$$

where x is the input variable, as was said before. The subscript j stands for the number of iterations, $f(x_j)$ stands for the critical buckling strength predicted by the LR model, and M stands for the amount of output data. The value of w has the least amount of loss over all iterations.

Support Vector Regression (SVR) –

Support Vector Regression (SVR), utilized in regression mode (SVR), were evaluated to address the nonlinear interactions among structural dimensions, stacking sequences, and damage initiation loads. The kernel approach lets SVR transfer the input space into a feature domain with more dimensions. This lets it find nonlinear stiffness–instability relationships that linear methods don't do a good job of describing. We looked at both linear and radial basis function (RBF) kernels to see how well they worked. The SVR method is a nonlinear classification technique that classifies test data into several categories. By establishing a nonlinear classification threshold from data comprising N independent variables projected into a higher-dimensional space and employing training data $\{(zk, qk)\}_{k=1}^N$, a linear model can be formulated [29], where z represents the independent variable and q denotes the classification vector, defined as $q_k \in \{-1, 1\}$. The categorisation is conducted for N samples. The classification is executed by establishing an optimal hyperplane as delineated by Equation (11). The optimal hyperplane must satisfy the requirements outlined in Equations (12) and (13).

$$g^T \phi(z_k) + h = 0 \quad (11)$$

$$g^T \phi(z_k) + h = 0 \geq 1 \text{ para } q_k = 1 \quad (12)$$

$$g^T \phi(z_k) + h = 0 \geq -1 \text{ para } q_k = -1 \quad (13)$$

where g is the weight vector. Equations (11)–(13) delineate the fundamentals of SVR. To effectively apply the SVR technique for predicting output parameters using regression of input parameters, a mapping function must be established. The mapping function $\phi(.) : \mathbb{R}^n \rightarrow \mathbb{R}^{nk}$. The rank, from independent variables to a higher-dimensional space, is established by integrating Equations (11)–(13) and is expressed as Equation (14):

$$q_k [g^T \phi(z_k) + h] \geq 1 \quad (14)$$

Equation (14), introduced by Vapnik [39], is utilised to categorise samples into two groups, but it is not suitable for deriving the best hyperplane equation. A tolerance margin $\beta \geq 0$ is incorporated into the classification threshold of Equation (14), resulting in Equation (15). The minimum of the g function for determining the ideal hyperplane may be computed using Equation (16).

$$q_k [g^T \phi(z_k) + h] \geq 1 - \beta_k \quad (15)$$

$$\min_{g,h} \frac{1}{2} \|g\|^2 + C \sum_{k=1}^N \beta_k \quad (16)$$

C is the tuning parameter for the optimal hyperplane categorisation as delineated in Equation (5). Patel et al. [30] and Huang and Tsai [31] demonstrated that employing $f(z, g) = g^T z + h$ as a linear regression function can yield improved predictions. Thus, a threshold mistake, which The ϵ -insensitivity loss function is employed. Should the ϵ -insensitivity loss function be delineated as Equation (17), the disparity between the classification vector q and the optimal hyperplane is between the interval defined by $-\epsilon - \beta_i^*$ and $\epsilon + \beta_i$ (Equation (18)).

$$|q - f(z, g)|_\epsilon = \begin{cases} 0, & \text{case } |q - f(z, g)| \leq \epsilon \\ |q - f(z, g)| - \epsilon & \text{otherwise} \end{cases} \quad (17)$$

$$-\epsilon - \beta_i^* \leq (g^T z + h) - q_i \leq \epsilon + \beta_i \quad (18)$$

β and β^* are equivalent under symmetric circumstances. The residual minimisation function is specified as Equation (19), and Support Vector Regression (SVR) seeks to identify the least residual within the bandwidth of β and β^* .

$$R = \frac{1}{2} \|g\|^2 + C \sum_{k=1}^N (\beta_i + \beta_i^*) \quad (19)$$

where R is the cost function. The tuning settings must be established to minimise the system output.

Ensemble Model –

An ensemble learning method was utilized to integrate the advantages of Linear Regression (LR) and Support Vector Regression (SVR) for enhanced prediction of buckling behavior. Two ensemble methodologies were evaluated: weighted averaging, which amalgamates predictions according on validation efficacy, and stacking, wherein the outputs of LR and SVR function as inputs to a ridge regression meta-learner. The ensemble utilizes linear regression to identify global linear trends and support vector regression to characterize localized nonlinear interactions, therefore enhancing prediction accuracy and robustness for intricate post-buckling datasets. A comparative analysis was conducted to assess the performance of the ensemble relative to individual models.

Result and Discussion

Mechanical Characterization

Tensile Strength Analysis –

Figure 4(a) illustrates the tensile strength and modulus of the composites. The stress-strain profiles of each sample are illustrated in Figure F3 in the supplementary data (S1). The incorporation of 0.75 wt.% rGO into the epoxy matrix enhanced the tensile strength of the BREC composite by 8.79% relative to the BEC composite. This improvement is due to enhanced stress transfer within the matrix, enabled by the uniform distribution of rGO, which serves as a reinforcing filler to augment load-bearing capacity. The tensile strength of the CBEC composite, incorporating 1 wt.% rGO-coated basalt fibers, improved by 17.27% relative to BEC, attributable to superior fiber-matrix adhesion. The rGO coating roughens the surface of the fibers, which helps them cling together and carry tensile stress. The CBREC composite, had the strongest tensile strength, a 23.45% increase over BEC, an 11.87% increase over BREC, and a 5.0% increase over CBEC. The dual rGO modification ensures synergistic stress distribution at the fiber-matrix interface and throughout the matrix, hence enhancing tensile performance. The Table T1 in supplemental data (S1) shows detailed properties.

Compression Strength Analysis –

Figure 4 (b) depicts the modulus and compressive strength of the composites. Figure F4 in the supplementary material (S1) illustrates the stress-strain profiles for each sample. The BREC composite, comprising 0.75 wt.% rGO inside the epoxy matrix, demonstrated a 4.63% enhancement in compressive strength relative to the BEC composite. This transpired due to rGO enhancing the matrix's rigidity. The CBEC composite, incorporating basalt fibers coated with rGO, exhibited a strength increase of 11.23% compared to the BEC composite, attributable to the enhanced interface between the fibers and matrix, facilitating more uniform weight distribution under compression. The CBREC composite displayed the greatest compressive strength, showing enhancements of 15.54%, 10.3%, and 3.87% relative to BEC, BREC, and CBEC, respectively. The composite demonstrates exceptional resistance to compressive loads owing to the augmented strength of the matrix and the enhanced adhesion

between layers. The experimental data is included in Table T1 of the supplementary materials (S1).

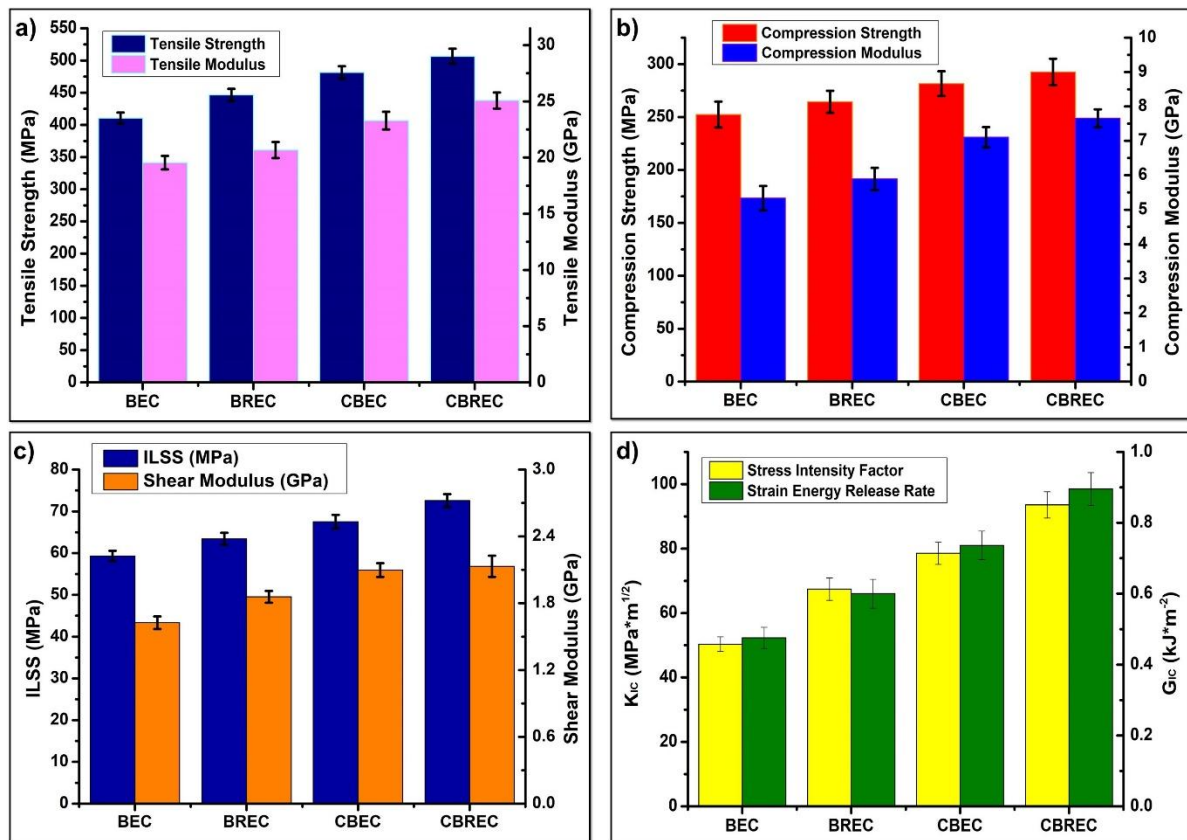


Figure 4: Mechanical characterization of composites (a) Tensile strength; (b) Compression strength; (c) ILSS ; (d) Fracture Toughness.

Interlaminar shear strength Analysis –

The ILSS is the laminate's layers' resistance to forces that try to move them. Figure 4 (c) shows the composites' ILSS values. Figure F5 in S1 shows each specimen's stress-strain contours. BEC composite interlaminar shear strength was 36.3 MPa. According to prior investigations on rGO-reinforced polymer composites, adding 0.75 wt.% rGO to the epoxy matrix increased ILSS by 7.4% for BREC compared to BEC due to strong interfacial bonding [26]. The CBEC composite's rGO coating on flax fibers increased ILSS by 13.9% over BEC and 6.12% over BREC. The rougher surface of rGO-coated fibers improves epoxy matrix incorporation. CBREC composite got the greatest ILSS at 72.4 MPa. This outperformed BEC, BREC, and CBEC composites by 22.09%, 13.65%, and 7.1%. CBREC has reduced fiber pull-out and improved fiber-matrix interlocking due to rGO's synergistic effect on fiber coating and matrix reinforcement. The supplementary material (S1) contains Table T1 with analysis data.

Fracture Toughness Analysis –

In Figure 4 (d), rGO dual-phase functionalization impacts critical strain energy release rate (G_{IC}) and fracture toughness-related stress intensity factor. The pristine basalt/epoxy composite (BEC) showed the lowest toughness, with a K_{IC} of $50.3 \text{ MPa}\cdot\text{m}^{1/2}$ and a G_{IC} of $0.51 \text{ kJ}\cdot\text{m}^{-2}$. The weak fiber-matrix interaction may reduce toughness. Adding rGO to the BREC epoxy matrix increased K_{IC} to $67.4 \text{ MPa}\cdot\text{m}^{3/2}$ and G_{IC} to $0.62 \text{ kJ}\cdot\text{m}^{-2}$, which enhances fracture pinning and deflection. The rGO-coated basalt/epoxy composite (CBEC) shown a significant improvement, with K_{IC} and G_{IC} reaching $78.6 \text{ MPa}\cdot\text{m}^{3/2}$ and $0.75 \text{ kJ}\cdot\text{m}^{-2}$, respectively. Improved fiber-matrix adhesion boosted fiber bridging and decreased fracture propagation. The dual-phase functionalized composite (CBREC) demonstrated high toughness, with a K_{IC} of $93.7 \text{ MPa}\cdot\text{m}^{3/2}$ and a G_{IC} of $0.91 \text{ kJ}\cdot\text{m}^{-2}$. This indicates K_{IC} outperforms BEC 86%. Synergy improves by strengthening the matrix and hardening the interphase. This distributes weight and prevents cracks. Figure F5 in supplementary material (S1) illustrates each sample's load-displacement contours. Duo-phase rGO functionalization usually turns brittle matrix breaking into energy-dissipative progressive failure.

Failure Mode Analysis and Interpretation

Figure 5 displays the SEM micrographs of cracked surfaces for BEC, BREC, CBE, and CBREC composites, emphasizing the progression of failure modes with rGO functionalization. The unaltered BEC composite (Fig. 5 a) demonstrates significant fiber pull-out and interfacial debonding, signifying inadequate fiber-matrix adhesion and ineffective stress transfer. In the BREC composite (Fig. 5 b), a partial enhancement is noted with localized fiber rupture; nonetheless, the occurrence of delamination indicates that matrix-only alteration offers restricted interfacial reinforcement. The CBE composite (Fig. 5 c) exhibits less fiber pull-out and enhanced fiber breakage, accompanied by matrix cracking, indicating superior interfacial bonding resulting from fiber surface modification. The dual-phase CBREC composite (Fig. 5 d) demonstrates predominant fiber fracture, robust interfacial adhesion, and cohesive fracture surfaces with negligible debonding, hence affirming enhanced load transfer efficiency and structural integrity. The lack of significant delamination and the occurrence of cohesive failure suggest improved resistance to crack propagation. These observations unequivocally indicate that dual-phase rGO functionalization markedly enhances the fiber-matrix interface, transforms the failure mode from interface-dominated to fiber-dominated mechanisms, and augments the mechanical performance and damage tolerance of the composite system.

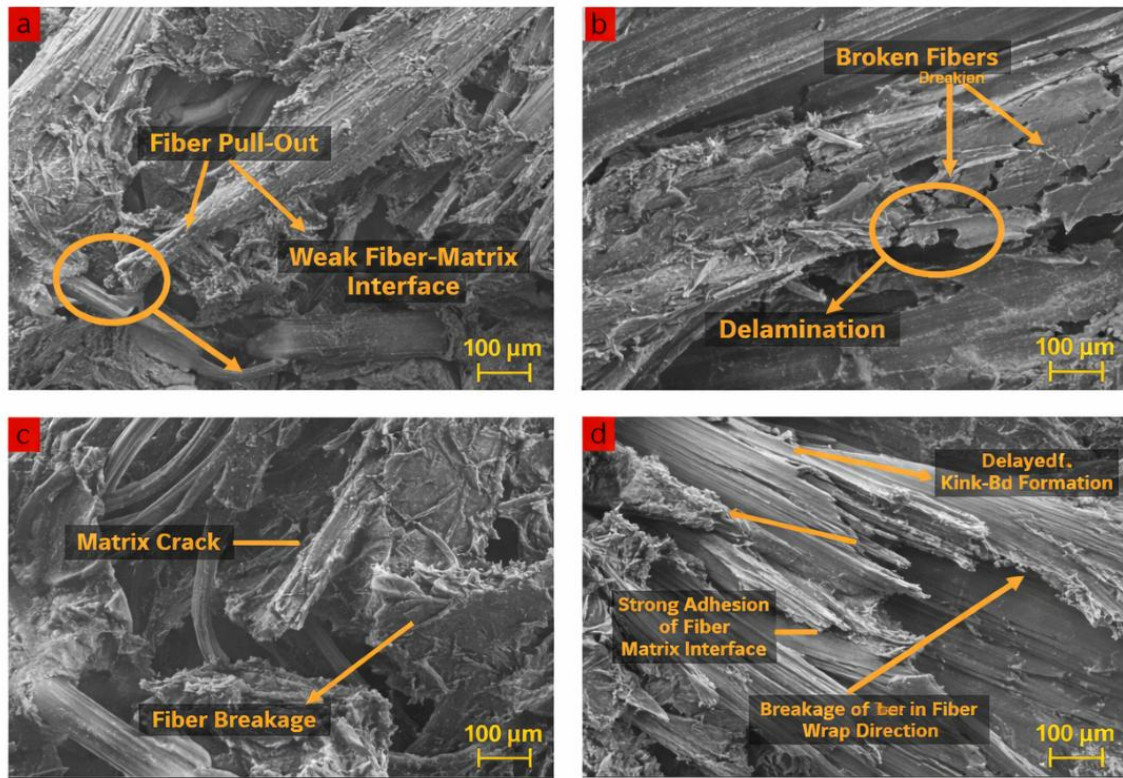


Figure 5: Characterization of the morphology of cracked BEC, BREC, CBEC, and CBREC composites (a) BEC; (b) BREC; (c) CBEC; (d) CBREC.

Non-linear Buckling Analysis of CBREC Composite

The experimental results demonstrated that the CBREC composite has superior mechanical strength, leading to its selection for further structural testing. To further confirm the impact of dual-phase rGO functionalization on improving compressive stability, a nonlinear buckling study was conducted utilizing the finite element method in ANSYS. This comprehensive method gives us a better understanding of what causes failures and shows that CBREC is a good choice for structural uses that need both great strength and reliable buckling resistance. Figures F2 in the supplementary information (S1) illustrate all of the properties of CBREC composites. ANSYS 2024 R1 was used to run a non-linear buckling simulation to acquire a clear idea of how stable the CBREC composite structure was by carefully modifying crucial design elements including length, width, thickness, and stacking sequence. The simulation dataset was created with 12852 design points and four main input parameters: laminate length (150 to 250 mm) with step size 2 mm; width (35 to 45 mm) with step size 0.5 mm; thickness (2.4–3.6 mm) with step size 0.6 mm; stacking sequence ($[90/45/0]_s$, $[0/45]_3$, $[0/90]_3$, and $[0/\pm 45/90]_s$). This implies it can be used for both light and heavy panels. The fiber volume percentage at was at 55%. These are instances of design choices that work well because they are strong, stiff, and easy to make. This study analyzes RVE-based model differences to accommodate material-level variability while preserving structural relevance.

FEM Validation and Convergence Studies –

The reliability of the nonlinear FEM framework was validated through mesh convergence and experimental comparison (Figure 6). Convergence analysis ensured numerical stability, with variations in critical buckling load maintained below 2.5%. Experimental and numerical load–deflection responses were compared for two configurations (Case A and Case B). The experimental curves exhibit an initial linear region followed by stiffness degradation near buckling, while FEM results show a linear response up to the critical load with subsequent plateau behavior. Predicted critical loads (1713 N and 2701 N) show reasonable agreement with experimental values (2003 N and 2411 N), with a maximum deviation of 14.5%. The discrepancies are attributed to manufacturing imperfections, material heterogeneity, and simplified damage representation. Overall, the FEM model accurately captures both pre- and post-buckling behavior, confirming its robustness for structural analysis and optimization.

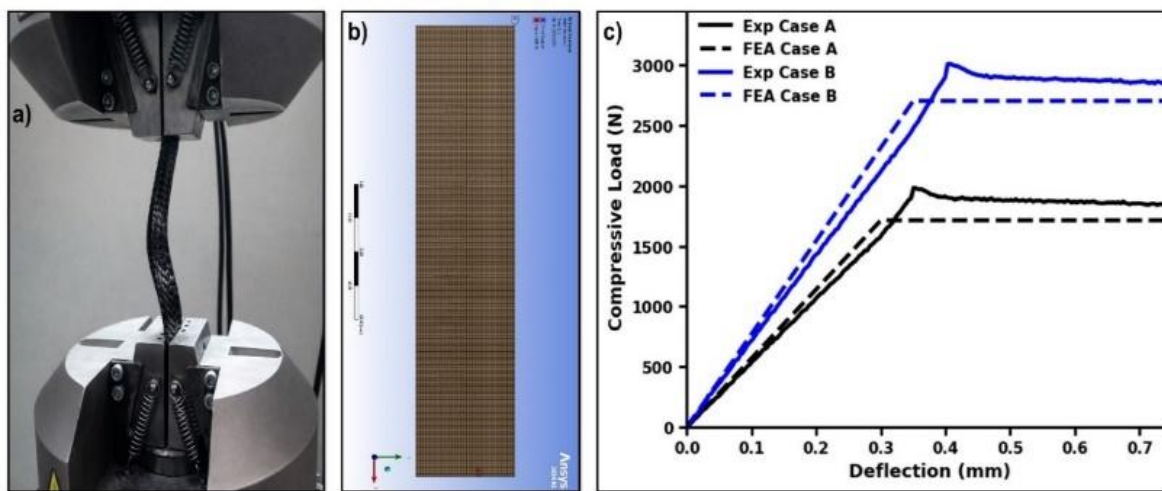


Figure 6: FEM validation of CBREC composites under axial compression: (a) Experimental setup; (b) Meshed model with boundary conditions; (c) Load-displacement curves from the simulation and experiment.

Machine Learning Model Analysis

The comparative analysis (Table 6) demonstrates that the ensemble model surpasses Linear Regression (LR) and Support Vector Regression (SVR), attaining superior R^2 values and reduced error metrics. As a result, later analyses concentrated on the ensemble model. Comprehensive diagnostics, encompassing actual versus predicted plots, residual analysis, correlation heat maps, and SHAP-based feature importance, were conducted to evaluate model performance and interpretability. The ensemble exhibited enhanced accuracy, equitable error distribution, and robust explanatory power, validating its dependability for forecasting buckling behavior.

Table 6: Validations of each ML models.

Model	Dataset	R ²	RMSE	MAPE	MAE
LR	Training	0.642	21.53	5.48	16.72
	Test	0.711	24.87	7.12	19.35
SVR	Training	0.861	11.34	2.15	9.42
	Test	0.842	12.76	3.08	11.85
Ensemble	Training	0.987	8.592	1.275	7.083
	Test	0.973	7.998	2.097	10.44

The ensemble machine learning (EML) model exhibited enhanced predictive accuracy in determining the critical buckling load of CBREC composites. The stacking method, integrating LR and SVR, proficiently identified nonlinear correlations between geometric and material factors. A robust association between anticipated and actual values is evident in Figure 7(a), aligning with the performance measures presented in Table 6. The error distribution (Figure 7(b)) is centered at zero, exhibiting a minimal mean bias ($\mu = -1.25$ N) and a standard deviation ($\sigma = 41.69$ N), signifying dependable and unbiased predictions.

Correlation Matrix and Feature Importance Analysis –

A correlation matrix was employed to assess the correlations between input parameters and critical buckling load (CBL), as illustrated in Figure 7(c). Length had the most significant correlation ($r = 0.81$), signifying its primary impact on buckling behavior, succeeded by breadth ($r = 0.54$). Conversely, thickness ($r = 0.03$) and stacking sequence ($r = -0.02$) exhibited minimal connection. The results reveal that global geometric characteristics, specifically length and width, predominantly determine buckling resistance, whereas stacking configuration exerts a relatively minor direct impact.

SHAP analysis was employed to measure the influence of input variables on the projected buckling load (Figure 7(d)). The findings indicate that length exerts the most substantial influence, whereas stacking sequence and thickness demonstrate relatively moderate effects with sporadic localized contributions. The distribution of SHAP values underscores the existence of nonlinear and interaction effects among input factors. The ensemble model attained significant prediction accuracy ($R^2 > 0.97$), validating its capacity to consistently represent the fundamental structural dynamics. The results substantiate the mechanical interpretation of laminate behavior and illustrate the efficacy of the suggested framework for precise and comprehensible buckling prediction and optimization.

Analysis of Robustness and Uncertainty –

Figure 8(a) illustrates that the ensemble model effectively encapsulates both global trends and local fluctuations in critical buckling loads, with the majority of FEM results residing within the $\pm 1\sigma$ uncertainty limits. This signifies enhanced prediction stability and less variability relative to individual models, affirming its appropriateness for effective design assessment. Figure 8(b) evaluates the resilience of the ML-optimized design against fluctuations in ply angle ($\pm 2^\circ$) and thickness ($\pm 5\%$). The findings indicate a progressive decline in buckling load as disturbances increase, while staying within a limited performance spectrum. The optimum

resides inside a plateau region, signifying a robust and resilient design that is unaffected by minor production discrepancies.

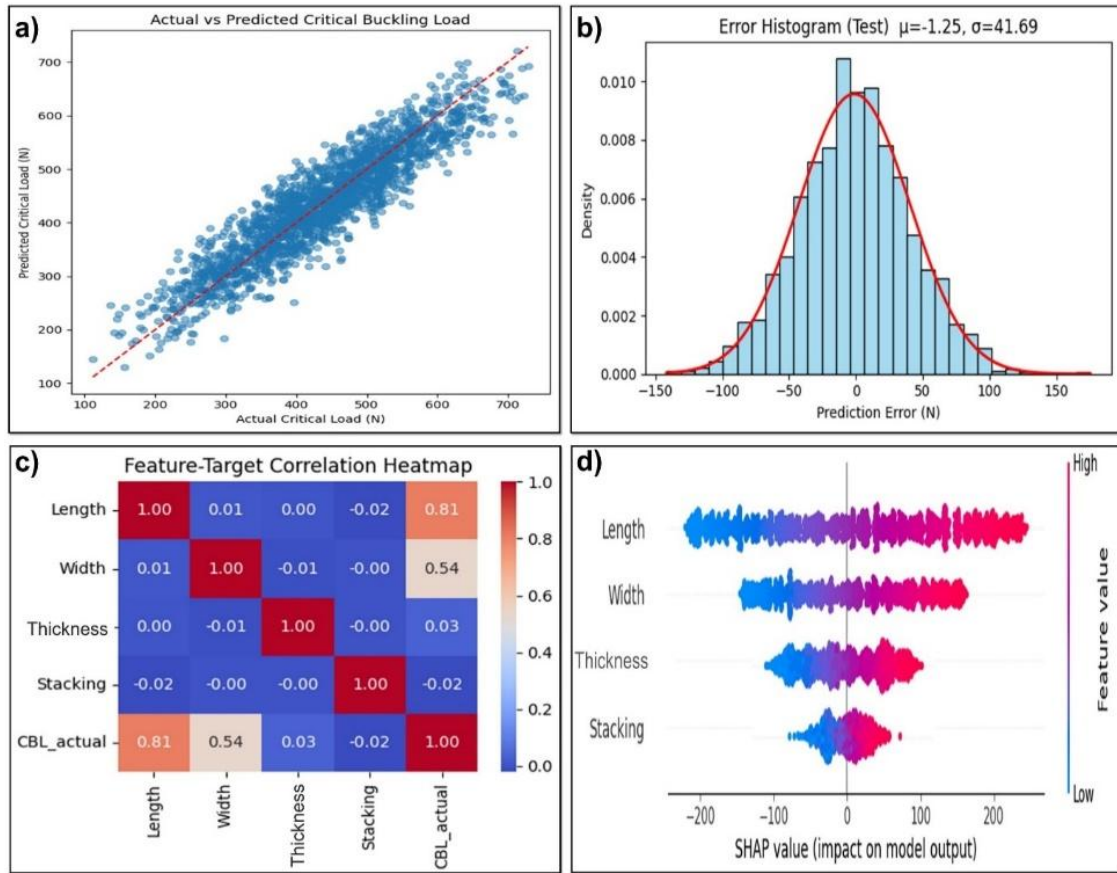


Figure 7: Model effectiveness. Ensemble model (a) actual against anticipated values; (b) Histogram error; (c) Correlation matrix; (d) SHAP.

ML-Driven Optimal Design Selection –

The ensemble model was employed to determine the ideal design configuration that enhances buckling performance within the investigated parameter space. The ML-driven optimization identified the stacking sequence of [90/45/0]_s, measuring $200 \times 40 \times 3$ mm, as optimal for achieving the maximum critical buckling stress while ensuring resilience to geometric and manufacturing discrepancies. Although the correlation study indicated a comparatively weaker direct effect of stacking sequence, the optimized configuration underscores its indirect yet essential role in regulating stress redistribution and structural stability via nonlinear interactions. A comprehensive progressive damage analysis was conducted to verify the structural integrity and failure characteristics of this ML-identified optimum. This facilitates a comprehensive understanding of how the optimized laminate bears load, originates damage, and finally progresses to failure under compressive loading circumstances.

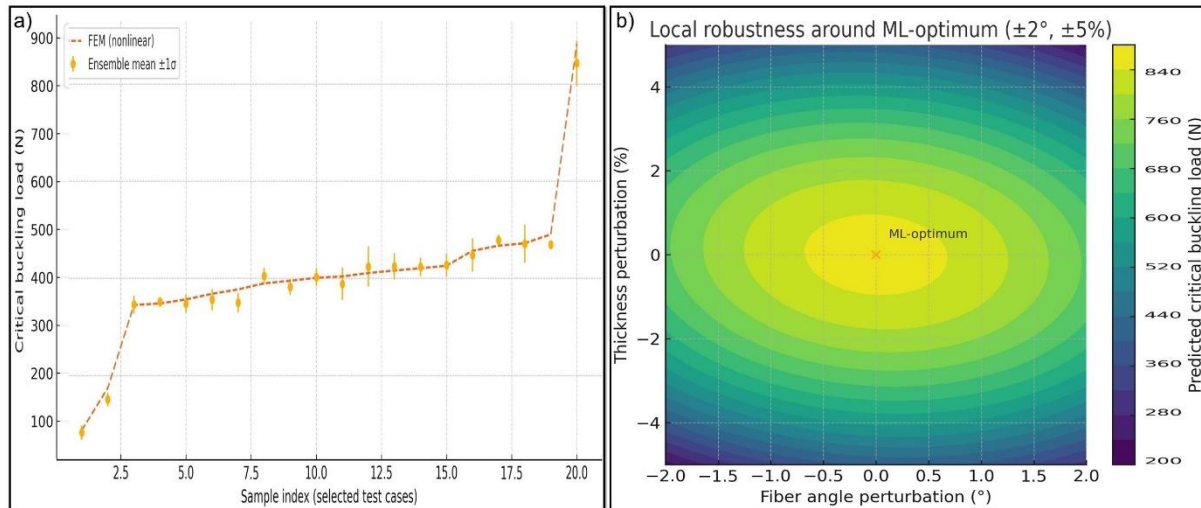


Figure 8: (a) Ensemble model prediction; (b) Local Robustness.

Damage Analysis

The machine learning-guided optimization determined the stacking sequence $[90/45/0]_s$ with dimensions of $200 \times 40 \times 3$ mm as the ideal arrangement for improving post-buckling capacity. A nonlinear progressive damage analysis was conducted in ANSYS to validate this prediction, utilizing Hashin's intralaminar failure criteria for precise monitoring of matrix- and fiber-dominated failure processes at the ply level. The course of damage, as depicted in Figures 9 (a) and 9 (b), demonstrates a distinct advancement mostly driven by matrix compressive failure. Figure 9 (a) illustrates that matrix compressive damage demonstrates the most significant growth rate with increasing load, whereas fiber compressive and tensile failure modes are relatively negligible, suggesting that the structural response is predominantly matrix-driven under compressive stress. Figure 9 (b) illustrates that outer and off-axis plies, especially those oriented at $\pm 45^\circ$ and 90° , exhibit greater vulnerability to early damage initiation due to elevated shear and transverse stress components, while 0° plies maintain their load-carrying capacity for extended periods. Table 7 shows ply-wise damage progression.

Table 7: Ply-wise damage progression under compressive loading.

Load (N)	Damage Stage	Ply 1	Ply 2	Ply 3	Ply 4	Ply 5	Ply 6
5725	Initiation (20%)	Low	Moderate	Low	Low	Moderate	Low
6638	Propagation (60%)	Moderate	High	Moderate	Moderate	High	Moderate
8213	Near-complete (95%)	High	Very High	High	High	Very High	High

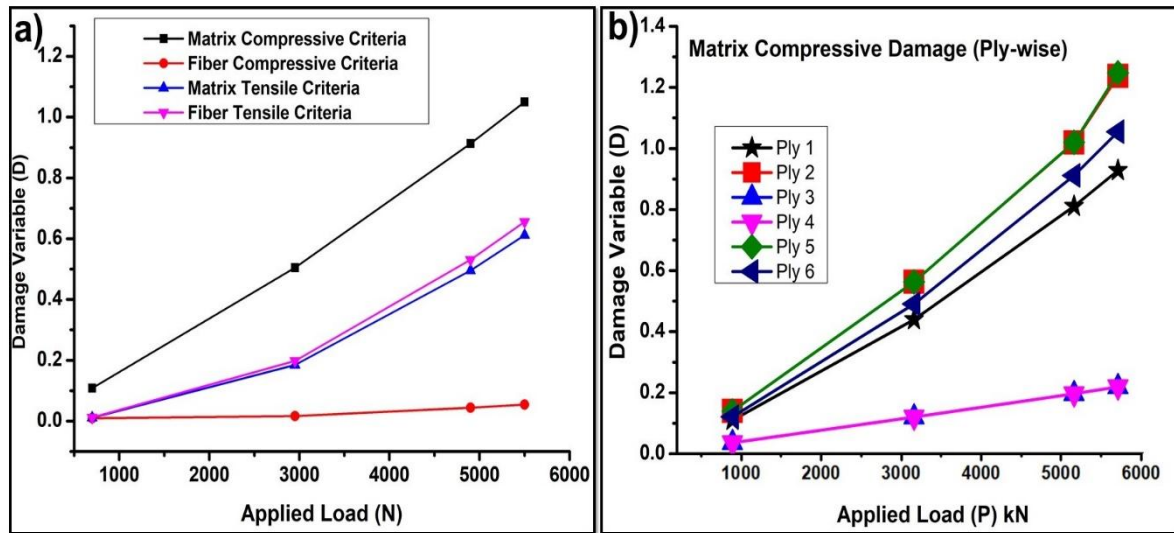


Figure 9: (a) Failure criteria. Hashin damage evolution; (b) Ply-wise matrix compressive failure.

The spatial progression of damage, illustrated in Figure 10, indicates that damage commences at certain corner regions at around 5725 N, impacting roughly 20% of the area and predominantly involving a restricted number of plies. As the load approaches 6638 N, damage proliferates markedly, affecting roughly 60% of the corner area with heightened ply contact and a decline in stiffness. At elevated loads (8213 N), damage permeates around 95% of the corner region, affecting all plies and signifying significant structural deterioration. The damage concentration at the corners is due to stress intensification from geometric limitations and boundary conditions, leading to premature matrix cracking and interlaminar stress accumulation. Ply-level measurements indicate that damage begins in off-axis plies and gradually extends to neighboring layers, resulting in a combined failure mechanism characterized by matrix cracking, fiber kinking, and interfacial deterioration.

Correlation Between Damage Evolution and ML Optimization

The progressive damage analysis offers essential understanding of the physical mechanisms that inform the ML-guided optimization outcomes. The ensemble learning model identified geometric parameters and stacking sequence as the primary elements affecting buckling performance; nonetheless, the damage analysis elucidates the structural superiority of the optimal configuration ([90/45/0]_s). The inclusion of off-axis plies facilitates stress dispersion and postpones catastrophic failure by encouraging slow matrix-dominated damage instead of sudden fiber-dominated collapse. The prevalent occurrence of matrix compression failure and its steady progression through the plies suggests that the optimized laminate functions within a damage-tolerant framework, characterized by a gradual rather than abrupt stiffness deterioration.

Moreover, the SHAP-based feature importance analysis indicated that geometric characteristics, including length and width, significantly affect buckling response, aligning with the observed damage localization in corner locations where stress concentrations peak. The machine learning model adeptly captures these nonlinear interactions, whilst the finite element method-based damage analysis offers the physical rationale for these trends. The interplay between data-driven prediction and physics-based interpretation illustrates that the

proposed FEM–ML paradigm is both predictive and mechanistically insightful. Thus, the amalgamation of machine learning with advanced damage modeling facilitates the discernment of laminate configurations that optimize structural integrity while ensuring regulated and postponed failure progression, crucial for the design of damage-tolerant composite structures.

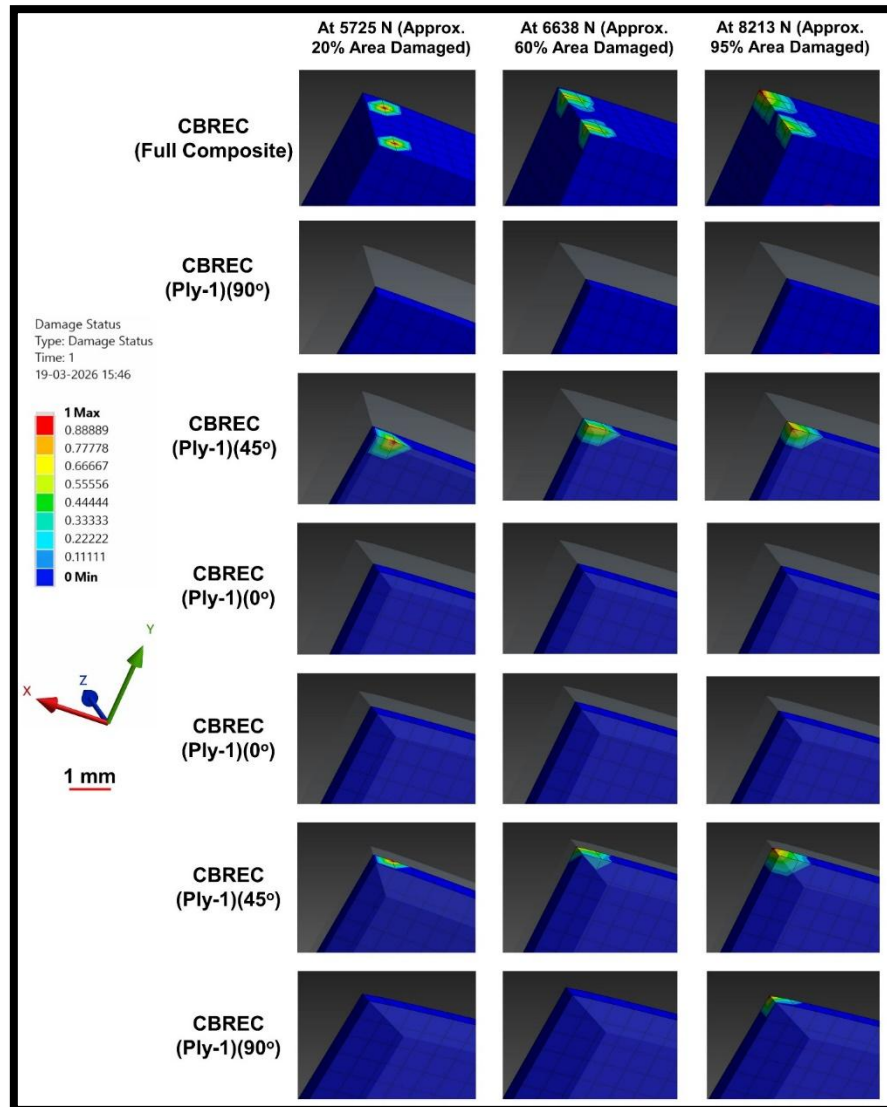


Figure 10: Progressive damage evolution and ply-wise corner localization.

Conclusion

This study developed and validated a comprehensive experimental–computational framework to investigate the influence of dual-phase reduced graphene oxide (rGO) functionalization on the mechanical performance, nonlinear buckling behavior, and progressive damage evolution of basalt/epoxy composites. Surface modification of basalt fibers through electrophoretic deposition combined with rGO reinforcement of the epoxy matrix produced a synergistic enhancement in composite performance by simultaneously strengthening the fiber–matrix

interface and increasing matrix stiffness. Mechanical characterization demonstrated that the dual-phase functionalized CBREC composite exhibited the highest tensile strength, compressive strength, interlaminar shear strength, and fracture toughness among all investigated configurations. Fractographic observations confirmed a transition from interfacial debonding and fiber pull-out in the unmodified composite to cohesive fiber-dominated failure mechanisms in the dual-phase functionalized system, indicating more efficient stress transfer and improved damage resistance. The experimentally optimized composite was subsequently integrated into a multiscale modeling framework. RVE-based homogenization successfully captured the influence of nanoscale reinforcement on the effective orthotropic properties used in nonlinear finite element simulations. The developed FEM model accurately reproduced the experimentally observed buckling response and provided detailed insight into damage initiation and propagation under compressive loading. Progressive damage analysis revealed that matrix compressive failure is the dominant damage mechanism, while dual-phase functionalization delays damage initiation and reduces the severity of failure propagation. To facilitate rapid design exploration, a large parametric database comprising 12,852 laminate configurations was generated and used to train machine-learning surrogate models. Among the evaluated models, the ensemble approach combining linear regression and support vector regression delivered the highest predictive accuracy, achieving an R^2 value of 0.973. SHAP-based interpretability analysis demonstrated that laminate length and width are the most influential parameters governing buckling performance, while stacking sequence contributes through nonlinear interactions. Machine-learning-driven optimization identified the [90/45/0]_s laminate with dimensions of $200 \times 40 \times 3$ mm as the most robust configuration for maximizing buckling resistance.

Overall, the proposed framework establishes a direct and traceable relationship between nanoscale material engineering, laminate-level structural behavior, and data-driven optimization. The integration of dual-phase graphene functionalization, multiscale finite element modeling, progressive damage analysis, and interpretable machine learning provides an efficient strategy for designing lightweight, damage-tolerant, and structurally efficient composite components for aerospace, automotive, marine, and civil engineering applications. Future work may extend the framework to impact, fatigue, and environmental loading conditions to further support the development of intelligent composite design methodologies.

Associated Content

Supporting Information:

The detailed fabrication process and stress-strain graph has been provided in the supporting information.

Disclosure Statement

The authors report there are no competing interests to declare.

Funding Resource

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflict of interest

The author declares that they have no conflict of interest.

Data Availability

All the data generated/analyzed during the study are available with the corresponding author upon reasonable request.

Declaration of generative AI and AI-assisted technologies in the writing process:

To increase readability, the authors employed QuillBot to polish language and paraphrase material. This publication's content is the authors' responsibility after utilizing this tool and reviewing and editing it.

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