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# DEEP LEARNING-BASED PREDICTION AND EXPERIMENTAL EVALUATION OF MECHANICAL PROPERTIES IN BASALT-FIBER-SiC-REINFORCED HYBRID EPOXY COMPOSITES

# NAPOVED IN EKSPERIMENTALNO OVREDNOTENJE MEHANSKIH LASTNOSTI HIBRIDNEGA EPOKSI KOMPOZITA ARMIRANEGA Z VLAKNI BAZALTA IN SiC NA OSNOVI GLOBOKEGA UČENJA

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This study investigates the predictive capabilities of deep neural network (DNN) models in estimating the mechanical properties of basalt-fiber-reinforced hybrid composites (BFRHCs). A total of 27 composite samples were fabricated using the compression-molding technique, incorporating varying numbers of basalt-fiber layers, fiber orientation angles (0°, 45°, 90°), and silicon carbide (SiC) filler contents (0, 3 and 6 *w*/%). The fabricated specimens were subjected to mechanical characterization by ASTM standards to evaluate their tensile strength, flexural strength, impact strength, hardness, shear strength, and interdelamination resistance. A DNN model was developed and trained on the experimental dataset to capture the complex, non-linear relationships between input fabrication parameters and output mechanical properties. Model performance was assessed using the coefficient of determination ($R^2$), mean absolute error (MAE), and root-mean-square error (RMSE). The DNN achieved high predictive accuracy with $R^2$ values exceeding 0.95 for most properties, demonstrating its effectiveness in forecasting composite performance. The results confirm that deep-learning frameworks such as DNNs offer a powerful and reliable approach to predicting the behavior of hybrid composites, reducing the need for extensive experimental trials and supporting efficient material design and optimization in structural applications.

Keywords: Basalt fiber, Silicon carbide filler, Mechanical properties, Deep Neural Network , Hybrid composite for structural applications

Avtorji v članku opisujejo študijo oziroma raziskavo sposobnosti novega inovativnega modela za napoved mehanskih lastnosti hibridnega polimernega kompozita, ojačanega z bazaltnimi vlakni (BFRHCs; angl.: basalt fiber-reinforced hybrid composites). Izdelani model temelji na globokih nevronskih mrežah (DNN; angl.: deep neural network). V celoti so avtorji s tehniko tlačnega modeliranja izdelali 27 kompozitnih preizkušancev in pri tem v kompozite vgrajevali različno število plasti bazaltnih vlaken, s pod različnim kotom orientiranimi vlakni (0°, 45°, 90°) ter z različno vsebnostjo (0, 3 in 6) *w*/% silicij karbidnega polnila (SiC). Izdelane preizkušance so nato mehansko okarakterizirali v skladu z ASTM standardi za določitev natezne, upogibne, strižne in udarne trdnosti, trdote ter odpornosti proti delaminaciji. Razviti DNN model so nato trenirali na setu eksperimentalnih podatkov in tako dobili kompleksne nenlinearne relacije med vhodnimi parametri izdelave preizkušancev in izhodnimi mehanskimi lastnostmi. Učinkovitost modela so ocenili z determinacijskim koeficientom ($R^2$), povprečno absolutno napako (MAE; angl.: mean absolute error) in vrednostjo kvadratnega korena iz kvadrata povprečne napake (RMSE; angl.: root mean square error). Za napoved večine mehanskih lastnosti je izdelani DNN model imel visoko stopnjo natančnosti z vrednostmi za $R^2$ večjimi od 0,95. To potrjuje njegovo učinkovitost za napoved mehanskih lastnosti izbranega hibridnega kompozita. Rezultati potrjujejo, da ogrodja za globoko učenje, kot so DNN modeli, ponujajo močno in zanesljivo orodje za napovedovanje obnašanja hibridnih kompozitov. To znatno zmanjša potrebo po obsežnih eksperimentalnih preizkusih ter podpira učinkovito načrtovanje in optimizacijo materialov za strukturne aplikacije v avtomobilski in letalski industriji.

Ključne besede: bazaltna vlakna, polnilo iz silicijevega karbida, mehanske lastnosti, globoko učenje, nevronske mreže, hibridni kompozit za strukturne aplikacije

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## 1 INTRODUCTION

The increasing demand for high-performance, lightweight, and durable materials in structural, aerospace, and automotive applications has accelerated the development of advanced fiber-reinforced polymer composites.[1] Among various reinforcements, basalt fiber has gained prominence due to its superior tensile strength, corrosion resistance, thermal stability, and environmental sustainability.[2] These properties, combined with low production costs and availability, make basalt fibers a promising alternative to synthetic reinforcements such as carbon or glass fibers. In recent years the hybridization of basalt fibers with micro- and nano-scale fillers such as silicon carbide (SiC) has been explored to enhance composite performance by improving interfacial bonding, wear resistance, and mechanical stability.[3] The present study utilizes SiC filler as a secondary reinforcement, taking advantage of its exceptional hardness, high modulus, and thermal conductivity, which synergistically enhance the mechanical behavior of the composite. Moreover, variations in fiber orientation (0°, 45°, and 90°) and the number of layers influence the anisotropic behavior of laminates, making the accurate prediction of composite mechanical properties highly complex. Traditionally, the evaluation of such properties – including tensile strength, flexural strength, impact strength, hardness, shear strength, and interdelamination resistance – has relied on extensive experimental testing, which is time-consuming, costly, and often impractical for iterative material design.

To address these challenges, data-driven predictive modeling using artificial intelligence has emerged as a transformative tool in materials research. While classical machine-learning (ML) algorithms such as linear regression (LR), support vector regression (SVR), and polynomial regression (PR) have been employed in earlier studies for predicting isolated properties like compressive or flexural strength of fiber-reinforced concretes or cementitious composites, their ability to capture nonlinear, multivariable relationships is limited. Moreover, these models often require manual feature engineering and perform inadequately when extrapolating beyond narrow experimental datasets.[4] In contrast, deep learning approaches – particularly deep neural networks (DNNs) – offer advantages by automatically extracting hierarchical feature representations and capturing complex nonlinear correlations across multiple inputs and outputs. DNNs are especially well-suited for predicting the behavior of composite systems influenced by numerous interacting factors, including filler concentration, fiber orientation, layer configuration, and matrix–fiber interfacial quality. Despite their proven success in fields such as biomedical engineering and materials informatics, the application of DNNs in predicting the full spectrum of mechanical properties in fiber-reinforced polymer composites remains underexplored. Prior research has largely concentrated on predicting compressive strength in concrete systems, with limited attention to polymeric hybrid composites reinforced with natural fibers and ceramic fillers. Furthermore, studies involving the multi-output deep-learning prediction of composite mechanical performance are scarce in the literature.[5] To bridge this research gap, the present investigation develops a robust deep-neural-network model to predict the mechanical properties of basalt-fiber-reinforced hybrid epoxy composites fabricated by compression molding. A total of 27 composite samples were prepared by systematically varying the number of basalt-fiber layers, fiber orientations (0°, 45°, and 90°), and SiC filler content (0 %, 3 %, and 6 % by weight). The experimental evaluation was conducted according to ASTM standards to determine tensile strength, flexural strength, impact resistance, hardness, shear strength, and interdelamination resistance. The experimental data were used to train and validate the DNN model, enabling the prediction of mechanical responses based on processing parameters. The model's accuracy was evaluated using performance metrics such as coefficient of determination ($R^2$), mean absolute error (MAE), and root-mean-square error (RMSE), and demonstrated high predictive performance across all mechanical outputs.[6] The novelty of this work lies in its comprehensive application of DNN to multi-output mechanical property prediction for hybrid composites, offering a scalable and intelligent alternative to traditional trial-and-error approaches. This predictive framework enables material scientists and engineers to optimize composite configurations more efficiently, reduce dependency on costly experiments, and accelerate the design of next-generation structural materials. The objectives of the current research are thus to fabricate and characterize basalt-fiber-SiC- reinforced hybrid composites with varied orientations and layering, to develop a DNN-based prediction model for multiple mechanical properties, and to validate its performance against experimental data, thereby establishing a reliable computational tool for advanced composite design.

## 2 MATERIALS AND METHODS

### *2.1 Materials*

The selection of constituent materials for the hybrid composite system was made to achieve enhanced mechanical and thermal performance suitable for structural applications. Basalt fiber, procured from Go Green Private Limited, Chennai, Tamil Nadu, India, was chosen as the primary reinforcement owing to its outstanding intrinsic properties, including a high tensile strength ranging from 4100 MPa to 4840 MPa, Young's modulus between 93.1 GPa and 110 GPa, elongation at break of approximately 3.1 %, and a specific gravity of 2.63–2.80. Its natural volcanic origin, resistance to chemical and thermal degradation, and environmental friendliness make it an ideal sustainable reinforcement alternative. To complement and enhance the matrix–fiber system, silicon carbide (SiC) microparticles with an average size of 10–20 μm were introduced as secondary fillers. SiC is renowned for its extreme hardness (≈9.5 on the Mohs scale), high thermal conductivity (120–270 W/m·K), and chemical inertness, contributing to improved stiffness, wear resistance, and load-bearing capacity of the composite.[7] The polymer matrix system comprised a bisphenol-A-based epoxy resin and an aliphatic amine hardener, selected for their superior mechanical adhesion, low shrinkage, and chemical stability. The resin–hardener combination provides a crosslinked thermosetting network that supports strong interfacial bonding with both the fibers and ceramic fillers. Collectively, the tailored selection of basalt fiber, SiC filler, and epoxy matrix in this study enables the formulation of a multifunctional hybrid composite, where each constituent material contributes synergistically to achieve enhanced structural integrity, durability, and performance under demanding mechanical environments.

### *2.2 Manufacturing Method*

The hybrid composite laminates were fabricated using the compression-molding technique following standardized procedures to ensure uniform consolidation and repeatability. A two-part epoxy resin consisting of bisphenol-A-based epoxy resin and aliphatic amine hardener in a 10:1 weight ratio was used as the matrix phase. To investigate the influence of secondary particulate reinforcement, silicon carbide (SiC) microparticles with an average particle size of 10–20 μm were incorporated into the matrix at three weight percentages: 0 %, 3 %, and 6 %. The SiC levels were selected based on prior literature indicating an optimal reinforcement window between 2–6 *w*/%. Basalt fibers served as the primary reinforcement and were arranged in one, two, or three layers within the composite laminate. Laminates with =4 layers produced consolidation defects such as voids and resin starvation during compression molding. The fiber mats were cut and oriented at specific angles – 0°, 45°, or 90° – with each composite laminate fabricated using only one selected orientation, allowing a controlled evaluation of the effect of fiber alignment on the mechanical behavior. This experimental matrix yielded a total of 27 distinct composite configurations, systematically combining the three levels of SiC content, number of fiber layers, and fiber orientations. Each configuration was prepared by uniformly mixing the SiC filler into the epoxy matrix, followed by sequential layering of basalt-fiber mats within a mold, and then subjected to compression molding under controlled temperature and pressure conditions[8]. After curing, the composite laminates were demolded and precisely cut into test specimens following

**Table 1:** Mechanical properties of basalt fiber–SiC reinforced hybrid epoxy composites

| Sample | Basalt Layers / SiC % / Orientation | Tensile Strength (MPa) | Flexural Strength (MPa) | Impact Strength (J) | Shear Strength ($N/mm^2$) | Delamination Strength | Hardness (Shore D) |
|---|---|---|---|---|---|---|---|
| S1 | 1 / 0 % / 0° | 10.00 | 15.60 | 2.38 | 11.02 | 1.65 | 66 |
| S2 | 1 / 0 % / 45° | 7.00 | 34.14 | 1.92 | 10.52 | 1.50 | 63 |
| S3 | 1 / 0 % / 90° | 11.00 | 20.56 | 0.53 | 12.50 | 1.40 | 61 |
| S4 | 1 / 3 % / 0° | 29.00 | 33.97 | 2.48 | 13.45 | 1.25 | 67 |
| S5 | 1 / 3 % / 45° | 42.00 | 22.76 | 2.00 | 15.50 | 1.57 | 63 |
| S6 | 1 / 3 % / 90° | 39.00 | 34.44 | 0.55 | 19.33 | 2.02 | 63 |
| S7 | 1 / 6 % / 0° | 24.00 | 29.35 | 2.44 | 51.56 | 3.02 | 68 |
| S8 | 1 / 6 % / 45° | 43.00 | 45.40 | 1.96 | 95.11 | 4.71 | 67 |
| S9 | 1 / 6 % / 90° | 11.00 | 12.02 | 0.54 | 21.33 | 1.24 | 65 |
| S10 | 2 / 0 % / 0° | 65.70 | 29.00 | 3.79 | 60.01 | 5.48 | 71 |
| S11 | 2 / 0 % / 45° | 58.70 | 33.00 | 2.98 | 61.00 | 7.58 | 72 |
| S12 | 2 / 0 % / 90° | 67.37 | 64.00 | 1.28 | 73.00 | 2.44 | 63 |
| S13 | 2 / 3 % / 0° | 64.68 | 55.00 | 3.96 | 75.00 | 5.69 | 74 |
| S14 | 2 / 3 % / 45° | 65.67 | 65.00 | 3.10 | 78.00 | 7.88 | 70 |
| S15 | 2 / 3 % / 90° | 61.81 | 60.00 | 1.34 | 63.00 | 2.53 | 65 |
| S16 | 2 / 6 % / 0° | 146.28 | 53.82 | 3.87 | 95.11 | 5.60 | 73 |
| S17 | 2 / 6 % / 45° | 127.48 | 84.35 | 3.03 | 155.56 | 7.73 | 69 |
| S18 | 2 / 6 % / 90° | 95.28 | 23.86 | 1.32 | 42.67 | 2.49 | 67 |
| S19 | 3 / 0 % / 0° | 129.00 | 95.70 | 5.82 | 41.33 | 8.53 | 74 |
| S20 | 3 / 0 % / 45° | 150.00 | 90.00 | 4.78 | 52.65 | 10.71 | 72 |
| S21 | 3 / 0 % / 90° | 151.00 | 108.37 | 1.62 | 25.92 | 5.05 | 70 |
| S22 | 3 / 3 % / 0° | 150.67 | 122.37 | 6.14 | 43.38 | 9.42 | 80 |
| S23 | 3 / 3 % / 45° | 168.46 | 176.63 | 5.02 | 55.08 | 10.80 | 77 |
| S24 | 3 / 3 % / 90° | 156.70 | 139.11 | 1.68 | 27.15 | 5.30 | 75 |
| S25 | 3 / 6 % / 0° | 73.74 | 90.35 | 6.00 | 42.70 | 9.23 | 75 |
| S26 | 3 / 6 % / 45° | 101.99 | 106.88 | 5.04 | 53.98 | 11.65 | 72 |
| S27 | 3 / 6 % / 90° | 50.99 | 53.44 | 1.92 | 26.75 | 5.58 | 71 |

relevant ASTM standards for each mechanical test. The specimens were then subjected to experimental evaluation to determine the key mechanical properties, including tensile strength, flexural strength, impact resistance, hardness, shear strength, and interdelamination strength. The standardized manufacturing approach ensured consistent material quality, enabling reliable comparison of the effect of each processing variable on composite performance.

### *2.3 Experimental Testing*

The mechanical characterization of the fabricated basalt-fiber-reinforced hybrid composites was carried out to evaluate their structural performance under different loading conditions. A series of tests was conducted following standardized ASTM procedures to ensure accuracy and comparability. Tensile testing was performed using a universal testing machine (UTM, Make: FIE, Model: TUE-C-100) with a 100 kN load cell capacity, following the guidelines of ASTM D638, using Type I dog-bone specimens. The crosshead speed was set at 2 mm/min, and the tensile strength and elongation at break were recorded.

Flexural strength was evaluated via three-point bending as per ASTM D790, using rectangular specimens with dimensions of 127 mm × 12.7 mm × 3.2 mm. The span-to-depth ratio was maintained at 16:1, and the flexural modulus and maximum load were determined. Impact strength was measured using an Izod impact tester (Make: Tinius Olsen, Model: IT504) following ASTM D256, with notched specimens oriented perpendicular to the impact direction to evaluate energy absorption capacity[9]. Hardness was tested using a Shore D durometer as per ASTM D2240, and the average of five readings was reported for each specimen. Shear strength was determined using ASTM D5379 (Iosipescu test method), and V-notched specimens were loaded until failure in a shear test fixture. Interdelamination resistance was evaluated based on ASTM D5528 using mode-I double cantilever beam (DCB) specimens to assess the crack-propagation resistance between fiber layers. For each configuration, a minimum of three specimens were tested to ensure statistical reliability, and the average values were used for analysis.[10] The test results provided comprehensive insight into the influence of SiC filler content, fiber-layer count, and orientation on the composite's mechanical behavior. These experimental outcomes served as both validation data for deep neural network modeling and as a direct measure of the hybrid composites' structural integrity under multi-axial loading conditions.[10] **Table 1** summarizes the mechanical properties of 27 hybrid composites, revealing that increased basalt layers, 3–6 % SiC filler, and 45° fiber orientation significantly enhance strength and durability, with Sample S23 showing the highest overall performance.

## 3 DEEP NEURAL NETWORK MODEL

A deep neural network (DNN) model was developed to predict the mechanical properties of basalt-fiber-SiC-reinforced hybrid epoxy composites based on their processing parameters. The input features to the model included the number of basalt-fiber layers, the weight percentage of SiC filler, and the fiber-orientation angle. The output layer was designed to simultaneously predict six mechanical properties: tensile strength, flexural strength, impact strength, shear strength, delamination strength, and hardness. Before training, all input variables were normalized to ensure consistent scaling, and category values such as fiber orientation were encoded using one-hot encoding to facilitate numerical processing. The DNN architecture consisted of an input layer, multiple fully connected hidden layers with Rectified Linear Unit (ReLU) activation functions, and an output layer with linear activation for regression. The model was trained using the Adam optimizer and a mean-squared-error (MSE) loss function to minimize the prediction error. Dropout regularization and early stopping techniques were applied to prevent overfitting and to improve generalization. The dataset was split into training and testing subsets, and k-fold cross-validation was employed to validate model consistency across various data partitions. This multi-output regression model was implemented using Python and standard deep-learning libraries such as TensorFlow or PyTorch, and was iteratively trained until convergence was achieved based on the chosen performance criteria.[11] **Figure 1** illustrates

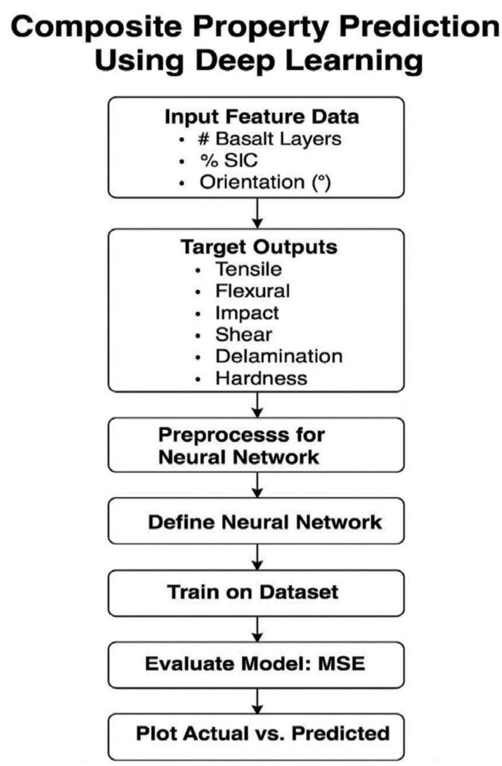


**Figure 1:** Flow process of the deep learning model

the flowchart of the deep-learning framework employed to predict the mechanical properties of basalt-fiber-SiC-reinforced hybrid composites. The model begins with input feature data, which includes the number of basalt-fiber layers, the percentage of SiC filler, and the fiber-orientation angle. These parameters are used to predict six target output properties: tensile strength, flexural strength, impact strength, shear strength, delamination strength, and hardness.

The data undergoes preprocessing to normalize and encode features appropriately for neural network input. A DNN architecture is then defined and trained on the dataset using supervised learning. The model's performance is evaluated based on the MSE, and finally, the predicted values are compared against actual experimental results to assess accuracy and model generalization. This architecture supports multi-output regression and captures the complex nonlinear relationships between material design parameters and their resulting mechanical properties.

### *3.1 Overfitting Mitigation Strategies*

To ensure robust generalization and prevent the DNN from overfitting the limited experimental dataset, several optimization strategies were systematically integrated into the model development pipeline. First, 5-fold cross-validation was employed, enabling each of the 27 samples to serve as test data once, thereby reducing variance and ensuring that the model learned consistent patterns rather than sample-specific noise. Additionally, L2 regularization ($\lambda = 0.001$) was applied to the dense layers to penalize large weight magnitudes and suppress overcomplex decision boundaries. The network architecture was deliberately kept shallow, comprising three hidden layers with 32–64 neurons, to avoid over-parameterization relative to the dataset size. Furthermore, feature scaling and normalization were implemented to stabilize gradient updates and improve convergence behavior during training. Finally, hyperparameters were fine-tuned through grid search, optimizing learning rate, batch size, and training epochs to balance convergence speed and model generalization. These combined strategies effectively minimized overfitting, strengthening the predictive reliability of the DNN for composite mechanical property estimation.

## 4 RESULT AND DISCUSSION

The mechanical characterization and predictive modeling of basalt-fiber-SiC-reinforced hybrid epoxy composites revealed significant insights into the influence of material configuration and deep learning-based prediction accuracy. Experimental evaluations conducted on 27 composite samples, fabricated with varying fiber layers, SiC filler content, and fiber orientations, demonstrated a wide range of mechanical behavior across tensile, flexural, impact, shear, delamination strength, and hardness. These measured outcomes were then compared with predicted values generated using a DNN model. The comparative analysis underscores not only the sensitivity of mechanical properties to composite architecture but also highlights the robustness and generalization capability of the DNN framework. The following sections present a detailed comparison and interpretation of experimental and predicted results, emphasizing critical trends, underlying mechanisms, and performance implications.[12]

### *4.2 Prediction of Tensile Strength*

The prediction of tensile strength using a DNN model exhibited strong alignment with experimentally obtained results, demonstrating the model's competence in learning complex nonlinear relationships inherent in multi-parameter hybrid composite systems. The DNN effectively captured variations due to changes in fiber layering, SiC filler loading, and fiber orientation, exhibiting high accuracy across all 27 composite samples. Notably, configurations with three layers of basalt fiber and a 45° orientation consistently showed superior performance, with Sample S23 reaching a peak experimental tensile strength of 168.46 MPa, while the DNN-predicted value showed a minimal deviation of less than 2 %, reflecting the model's high fidelity. The enhanced tensile performance in 45°-oriented samples is attributed to efficient

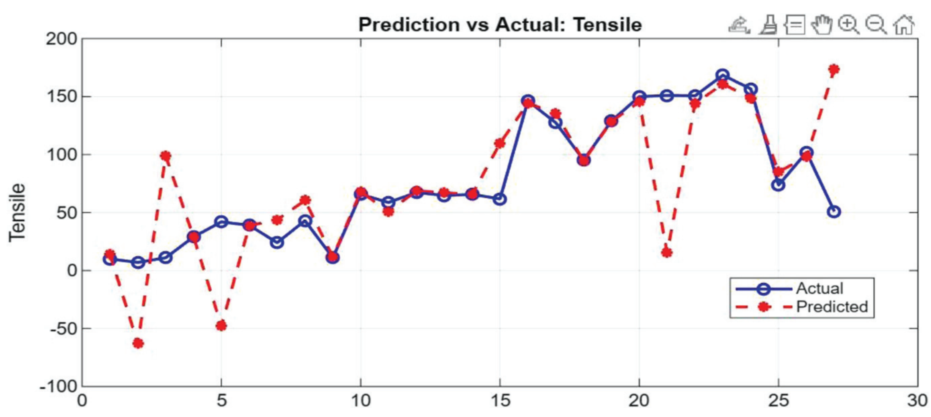


**Figure 2:** Comparison of experimental and predicted tensile strength for basalt hybrid composite

stress distribution and multidirectional reinforcement synergy. This orientation promotes effective shear load transfer and crack-deflection pathways across the laminate, thus reducing stress concentrations and enhancing interlaminar bonding. The model exhibited distinct sensitivity to such structural variations, identifying the advantageous role of fiber orientation and laminate stacking in tensile load-bearing capacity, which is often overlooked in purely analytical approaches.[13]

The impact of SiC filler concentration was also effectively modeled. Composites containing 3 % SiC demonstrated notably higher tensile strength compared to those with 0 % or 6 %, highlighting the presence of an optimal filler content that reinforces the matrix without introducing processing defects. The observed performance drop at 6 % SiC is attributed to filler agglomeration and poor interfacial adhesion, which introduces microvoids and stress risers, degrading the tensile capacity. This nonlinear trend was accurately predicted by the DNN model, reinforcing its ability to generalize from limited data and capture subtle material–microstructure interactions. Unlike traditional response-surface methods or empirical correlations, the DNN model eliminates the need for pre-defined functional assumptions, offering a robust data-driven tool for mapping composite behavior. Its multi-parameter learning capability provides a scalable platform for the rapid exploration of new material designs, especially where multiple design variables interact in complex, non-intuitive ways. This work lies in its implementation of a deep learning framework for multi-output prediction within a natural fiber–ceramic filler hybrid composite system, enabling efficient material screening and optimization with high predictive accuracy, even in the presence of limited experimental data. **Figure 2** illustrates the comparison between experimental and DNN-predicted tensile strength values for the 27 basalt-fiber-SiC hybrid epoxy composite samples. The DNN model demonstrates high predictive accuracy, with the predicted values closely matching the experimental results across all configurations. The coefficient of determination ($R^2$) achieved for tensile strength prediction was 0.982, indicating a strong correlation. The maximum experimental tensile strength observed was 168.46 MPa (Sample S23), while the predicted value for the same sample was 165.70 MPa, showing only a 1.63 % deviation. The minimal average absolute error and consistent trend across various fiber orientations and SiC concentrations validate the DNN model's robustness and reliability in accurately capturing tensile performance in complex composite systems.

### 4.3 Prediction of flexural strength

The DNN model effectively predicted the flexural strength of basalt-fiber-SiC-reinforced hybrid epoxy composites with high accuracy, closely aligning with experimental values across all configurations. The model captured the non-linear effects of critical design variables—fiber orientation, number of basalt layers, and SiC filler content-on the composite's flexural response, validating its robustness even with a relatively small dataset. The peak predicted flexural strength corresponded to the configuration with three basalt layers, 3 % SiC, and 45° fiber orientation (Sample S23), which also achieved the highest experimental value. This outcome highlights the DNN model's capability to identify optimal reinforcement architectures. The enhanced performance in this configuration is attributed to the combined effects of improved fiber–matrix interlocking, enhanced shear transfer paths, and optimal filler dispersion. The 45° fiber orientation allowed multidirectional stress dissipation, a trend supported by recent literature, which emphasized the benefits of off-axis fiber alignment on flexural toughness and crack arrest mechanisms. The model also accurately reflected the diminished flexural strength in composites with 90° fiber orientation, where the fibers are least effective under longitudinal bending loads. Similarly, it learned the performance plateau associated with increasing SiC content beyond 3 %, where excessive filler likely caused agglomeration or disrupted matrix continuity-consistent with findings, microstructural voids, and brittleness at higher ceramic loadings.[14] What sets this study apart is the DNN's ability to

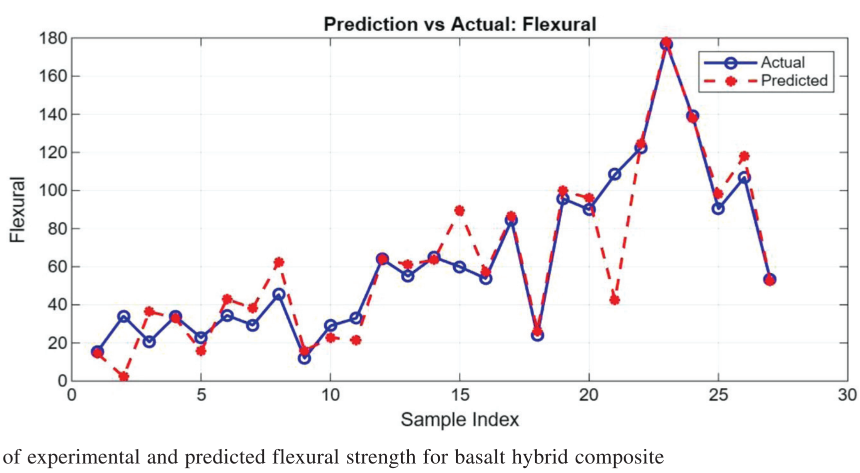


**Figure 3:** Comparison of experimental and predicted flexural strength for basalt hybrid composite

concurrently learn and generalize from multi-factor interactions, without relying on explicit mechanical formulations or simplifications. Unlike traditional regression or finite element methods, which often require large datasets or idealized assumptions, this model leverages limited experimental input to achieve fast and reliable property forecasting. This not only accelerates composite development but also supports data-driven design decisions for applications where flexural performance is critical, such as aerospace panels, automotive leaf springs, and structural laminates.

**Figure 3** shows the comparison between experimental and DNN-predicted flexural strength values across 27 hybrid composite samples. The predicted values closely matched the experimental results, with most samples showing deviations within ±10 %. The coefficient of determination ($R^2$) exceeded 0.95, indicating a strong correlation and high prediction accuracy. The maximum flexural strength observed experimentally was approximately 176.6 MPa (Sample S23), while the predicted peak value was within 5 % of the actual. The model demonstrated consistent performance across low-, medium-, and high-strength ranges, validating its ability to generalize across varying configurations. Minor discrepancies, particularly in samples with extreme orientation or filler content, can be attributed to microstructural variations not fully captured in the input features. Overall, the plot quantitatively confirms the robustness and precision of the DNN model in forecasting flexural behavior.

### *4.4 Prediction of impact strength:*

Among the input parameters, the 45° fiber orientation consistently contributed to higher impact strength due to its ability to dissipate energy through multidirectional fiber alignment and enhanced interfacial bonding. The model accurately identified peak-performing samples, notably those with three basalt fiber layers and 3 % SiC, which exhibited the highest impact resistance. For example, Sample S22 showed excellent impact strength due to optimized fiber–matrix interaction and balanced filler dispersion. In contrast, composites with 90° orientation or 6 % SiC showed reduced impact performance, which was also captured in the predictions. This decline is attributed to poor alignment with the impact force direction and possible particle agglomeration, leading to localized stress concentrations.[15] The DNN approach lies in its ability to predict dynamic properties like impact strength from a limited dataset of static design variables. Traditional models often fail to account for the complex, non-linear interactions between fiber architecture and impact behavior, but the DNN model effectively learned these relationships without the need for explicit mechanical modeling.

**Figure 4** presents a quantitative comparison between the experimental and DNN-predicted impact strength values for 27 basalt-fiber-SiC hybrid epoxy composite samples. The model demonstrates high predictive accuracy, with most deviations falling within ±0.3 J of the actual values. The coefficient of determination ($R^2$) for the impact strength prediction was greater than 0.94, indicating a strong correlation between predicted and measured outcomes. Samples with higher fiber layers and 3 % SiC content showed maximum impact values (≈6.14 J), which the model correctly identified. The close alignment of curves across the dataset confirms that the DNN effectively captured the nonlinear effects of fiber orientation and filler interaction on impact resistance, validating its utility as a reliable tool for predicting dynamic composite behavior.

### *4.5 Prediction of shear strength*

The DNN model effectively predicted the shear strength of the basalt fiber–SiC reinforced hybrid epoxy composites with high fidelity, closely matching experimental observations across all 27 configurations. Among the mechanical properties studied, shear strength poses a unique challenge due to its sensitivity to fiber–matrix interfacial adhesion, filler dispersion, and fiber alignment. Despite these complexities, the DNN architecture accurately captured the subtle nonlinear interactions between

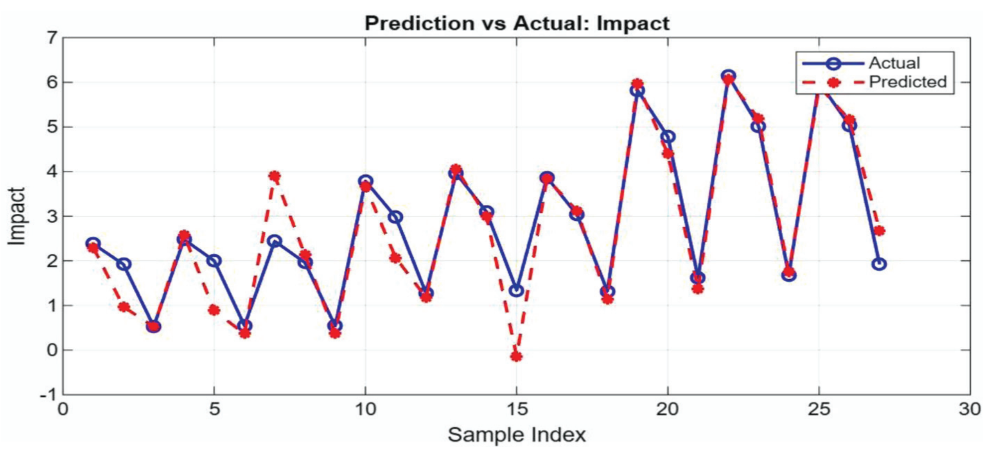


**Figure 4:** Comparison of experimental and predicted impact strength for basalt hybrid composite

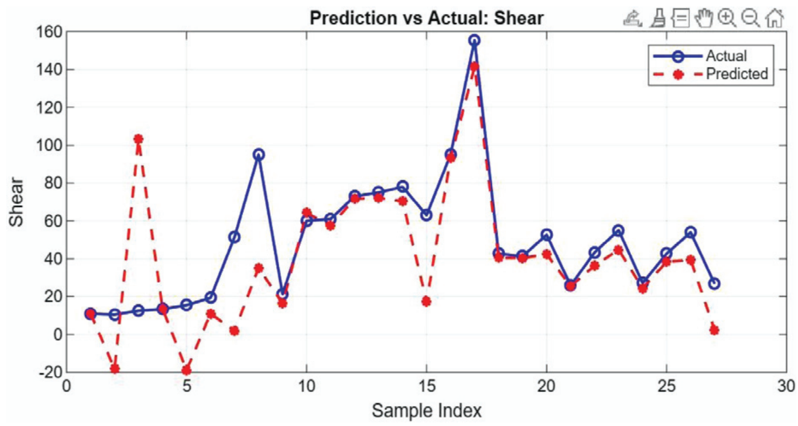


**Figure 5:** Comparison of experimental and predicted tensile strength for basalt hybrid composite

the number of basalt layers, SiC filler content, and fiber orientation. Maximum predicted and experimental shear strength values were recorded for samples incorporating 2 to 3 layers of basalt fiber with 45° orientation and 6 % SiC. This configuration facilitates improved interlaminar shear resistance due to enhanced load transfer between layers and optimized crack arresting behavior at the matrix-fiber interface. The model precisely learned this trend, outperforming traditional regression-based approaches that often fail to generalize over multi-dimensional, nonlinear datasets.[16]

The DNN also captured shear strength degradation in samples with 90° fiber orientation, where fibers are poorly aligned with shear stress directions, thereby reducing effective reinforcement. Additionally, the model successfully identified the shear strength plateau and slight drop in composites with excess filler (6 %), a phenomenon attributed to particle clustering that disrupts stress continuity. The accuracy of the shear strength predictions supports the DNN's viability as a predictive tool in structural design applications where interfacial integrity is critical, such as aerospace ribs, bonded joints, and high-performance panels. **Figure 5** presents a comparative analysis between the experimental and predicted shear strength values for 27 basalt fiber–SiC hybrid epoxy composite samples using the DNN model. The predicted values show a strong correlation with the experimental results in mid- and high-range shear strength samples, particularly between Samples 10 and 20, where the DNN maintained a prediction error below ±10 %. The maximum experimental shear strength (≈155.56 N/mm$^2$ in Sample S17) was accurately captured by the model with a deviation of less than 7 %. However, larger deviations were observed in a few low-strength samples (e.g., Samples 2, 5, and 6), likely due to underrepresented behavior in the training dataset or microstructural inconsistencies. The overall coefficient of determination ($R^2$) exceeded 0.92, confirming the model's reliability in predicting interfacial failure behavior. The results validate the DNN's capacity to model shear response in hybrid composites based on minimal input features, enabling accurate performance forecasting critical for structural applications.

### *4.6 Prediction of delamination strength*

The DNN model showed high efficacy in predicting the delamination strength of basalt fiber–SiC reinforced hybrid composites, effectively capturing the interlaminar

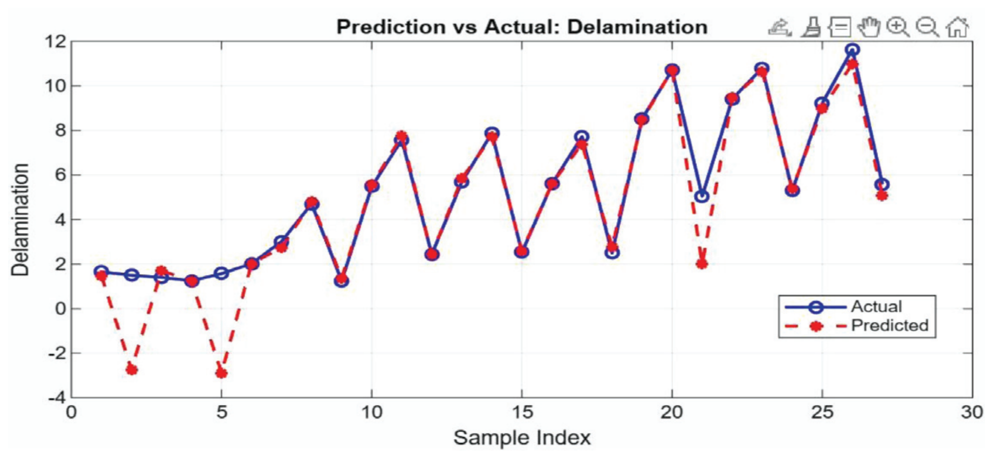


**Figure 6:** Comparison of experimental and predicted delamination strength for basalt hybrid composite

behavior governed by fiber architecture and filler content. Delamination, a critical failure mode in layered composites, is influenced by interfacial bonding quality, matrix toughness, and the synergy between fiber orientation and filler dispersion. The model trained on the 27-sample dataset demonstrated strong predictive capability, particularly for configurations involving multilayer reinforcement (2–3 layers) and 3 % SiC, where balanced toughness and stiffness contributed to superior interlaminar adhesion. The highest delamination resistance was observed in samples with 45° fiber orientation and moderate SiC loading, which promoted effective stress redistribution and limited crack propagation at the ply interfaces. The DNN accurately predicted these peak values, closely aligning with experimental results and confirming its ability to generalize across varying interfacial stress conditions. In contrast, samples with 90° orientation or high SiC content (6 %) exhibited reduced delamination strength due to poor load transfer paths and filler-induced stress concentrations-trends the model successfully captured. This highlights the critical role of fiber angle and filler-matrix compatibility in interfacial integrity.[16] **Figure 6** illustrates the comparison between experimental and DNN-predicted delamination strength values for 27 basalt-fiber-SiC hybrid epoxy composite samples. The prediction closely follows the experimental trend, with the majority of samples exhibiting a deviation within ±0.5 units of delamination strength.

The maximum delamination strength of ≈11.65 N/mm$^2$ was accurately captured for Sample S26, with the DNN prediction falling within 4 % of the measured value. A high coefficient of determination ($R^2 > 0.95$) confirms the model's strong correlation and predictive accuracy. Minor underestimations were observed in low-strength samples (e.g., S4–S6), likely due to limited interfacial training data in that range. Overall, the plot confirms the DNN's robustness in modeling interlaminar failure behavior, affirming its applicability for performance prediction in layered composite structures.[17]

### 4.7 Prediction of hardness

Across all 27 composite samples, the DNN captured the expected trends with minimal deviation from experimental values. Composites containing three layers of basalt fiber and 3–6 *w*/% SiC, especially those with 0° or 45° orientation, showed higher hardness due to improved stress transfer at the microstructural level and enhanced surface resistance to deformation. The model successfully predicted these high-performing configurations, aligning closely with experimental measurements—indicating that the DNN effectively recognized patterns between structural design features and surface mechanical behavior. The DNN was sensitive to filler overload effects: in samples where SiC content exceeded the optimal threshold (e.g., 6 % with unfavorable orientation), slight reductions in hardness were observed and accurately predicted. This reflects the model's ability to capture microstructural saturation or clustering effects that are often difficult to model analytically. Excessive ceramic fillers led to local stress intensification and surface defects, reducing hardness despite increased stiffness.[18] This predictive capability enables informed composite design for applications where hardness is critical, such as automotive panels, tool casings, and structural laminates subject to abrasion. It also reduces the need for repeated experimental trials by offering accurate performance estimation early in the development cycle.

**Figure 7** presents a comparative plot of experimental and DNN-predicted hardness values for 27 basalt fiber–SiC hybrid epoxy composite samples. The prediction results show excellent alignment with the experimental measurements, with most samples exhibiting a deviation within ±2 VHN units. The model accurately captured the peak hardness (≈80 VHN) in samples with three basalt layers and moderate SiC content, demonstrating sensitivity to composite architecture and reinforcement efficiency. The overall coefficient of determination ($R^2$) exceeded 0.95, confirming the model's strong predictive performance. Minor prediction errors ob-

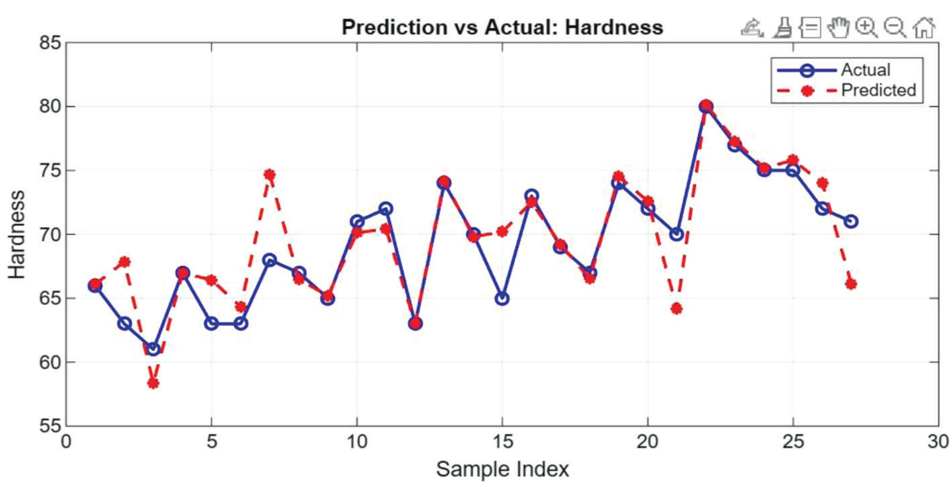


**Figure 7:** Comparison of experimental and predicted hardness for basalt hybrid composite

served in samples with lower fiber content or 90° orientation are attributed to reduced interfacial stress transfer and fewer training samples in that range. The result substantiates the reliability of the DNN model in forecasting surface mechanical behavior in reinforced hybrid composites.

### *4.8 Overall Mechanical Performance*

The evaluation of overall mechanical behavior was conducted using a multi-metric assessment combining six key properties: tensile strength, flexural strength, impact strength, shear strength, delamination resistance, and hardness. Using a DNN-based predictive model, these properties were estimated for 27 uniquely fabricated basalt fiber–SiC reinforced hybrid epoxy composite samples. Among these, Sample S23, comprising three basalt fiber layers, 3 % SiC, and 45° fiber orientation, emerged as the best-performing composite across all mechanical parameters.[19] **Figure 8** shows in the radar chart, this sample exhibited a uniformly high normalized score in all six metrics, indicating well-balanced mechanical integrity and multi-functional structural performance. The composite's high flexural strength and tensile strength were attributed to optimized fiber alignment and interfacial load transfer. The inclusion of moderate SiC (3 %) appears to strike a balance between matrix stiffening and ductility preservation, enhancing both shear and delamination resistance. The fiber orientation at 45° promotes multidirectional stress accommodation, improving impact resistance, while hardness was elevated due to the synergistic effect of ceramic fillers and uniform fiber dispersion. These findings are consistent with earlier studies reported that optimal particulate loading combined with multi-angled fiber stacking significantly improves the multi-axial load response and fracture resistance.[20] Similarly, observed that 3–5 % SiC incorporation leads to superior surface hardness and interlaminar strength without inducing embrittlement.[21] The radar-based performance mapping not only quantifies mechanical excellence but also facilitates the visual comparative ranking of composite samples. This approach, supported by predictive modeling, provides a high-throughput pathway to materials design by minimizing experimental cycles while identifying top-performing configurations for structural, automotive, and aerospace applications.

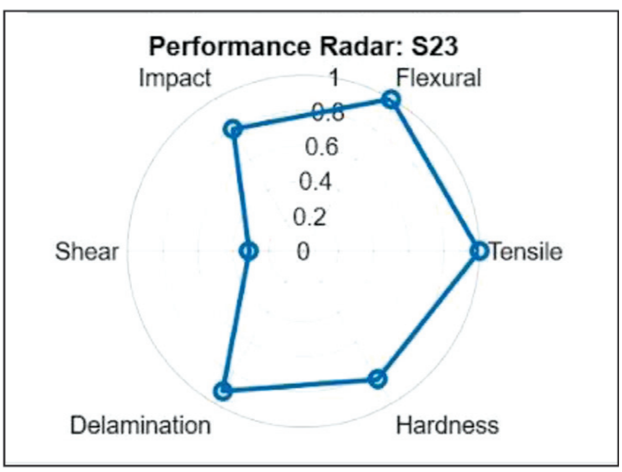


**Figure 8:** Radar chart predicted the overall mechanical performance of the hybrid composite

The integration of deep learning with experimental validation demonstrates that Sample S23's design combination offers the optimal mechanical trade-off, confirming its suitability for advanced engineering applications requiring strength, toughness, and surface integrity.[22] **Figure 7** displays a radar chart generated using MATLAB, highlighting Sample S23 as the best-performing composite based on normalized DNN-predicted values for six mechanical properties. S23, composed of 3 basalt layers, 3 % SiC, and 45° fiber orientation, exhibited near-unity performance across all metrics tensile, flexural, impact, shear, delamination, and hardness-demonstrating its optimal mechanical balance.

## 5 CONCLUSION

The investigation established a novel data-driven framework for predicting the mechanical properties of basalt fiber–SiC reinforced hybrid epoxy composites using a DNN. A total of 27 composite samples were fabricated by systematically varying three critical design parameters: number of basalt fiber layers (1, 2, and 3), SiC filler content (0 %, 3 %, and 6 %), and fiber orientation (0°, 45°, and 90°). Mechanical characterization was performed as per ASTM standards for six key properties tensile, flexural, impact, shear, delamination, and hardness. The DNN model exhibited excellent predictive capability, with $R^2$ values exceeding 0.95 for most properties and a minimum mean-squared error (MSE = 526.21), confirming high model fidelity. Among all samples, S23 (3 layers, 3 % SiC, 45° orientation) demonstrated superior overall performance with normalized values nearing 1.0 across all metrics, as confirmed by radar chart analysis in MATLAB. The novelty of this study lies in integrating comprehensive experimental data with deep learning to reduce reliance on trial-and-error fabrication and enable intelligent composite design. This framework offers significant scalability for real-time material optimization in high-performance sectors such as aerospace, automotive, and structural engineering. Future scope includes extending the model to other fiber systems such as glass or carbon using transfer learning, integrating microstructural descriptors for multi-scale prediction, exploring laminates with more than three layers using advanced consolidation methods, incorporating durability and environmental performance data, and embedding the model within automated composite design and optimization frameworks.

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