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# Investigation of Mechanical Properties of Banana, Linen and Their Hybrid Reinforced Composite Laminates in Adverse Condition and Analyze Using ML

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***Abstract***

*This research investigates the mechanical performance of composite laminates reinforced with banana and linen fibers, focusing on both individual and hybrid fiber combinations. The primary objective is to assess how these natural fiber composites behave under extreme environmental conditions, particularly high humidity and fluctuating temperatures, which are common in aerospace and automotive applications.Key mechanical properties—tensile strength, flexural strength, and impact resistance—are experimentally evaluated to assess the performance and long-term reliability of each composite design. Special attention is given to the synergistic effects that may arise when banana and linen fibers are combined, potentially leading to improved strength, toughness, and resistance to environmental degradation.To further enhance material evaluation and design, the study integrates machine learning (ML) techniques, such as regression models and classification algorithms, trained on the experimental dataset. These tools are used to predict and optimize mechanical properties based on input variables such as fiber type, environmental exposure, and fiber volume fraction. ML not only accelerates the material development process but also provides insights into performance trends, enabling designers to make informed decisions without relying solely on exhaustive physical testing. By combining experimental validation with data-driven modeling, this research offers a robust framework for the development of eco-friendly, high-performance composite materials. The findings contribute to the growing body of knowledge supporting the adoption of natural fiber-reinforced composites in structural applications, promoting sustainability and resource efficiency in engineering design. This work thus lays a foundation for future innovations in green composite technology.*

**Keywords**: Natural fiber composites, hybrid laminates, mechanical properties, tensile strength, environmental durability, machine learning optimization

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## INTRODUCTION

The increasing need for eco-friendly materials in sectors like aerospace, automotive, and construction is driving researchers and manufacturers to explore substitutes for conventional synthetic composites. Natural fiber-reinforced composites (NFRCs) have emerged as a promising solution due to their environmental advantages, including biodegradability, low density, and the potential for carbon neutrality. Among the various natural fibers, banana and linen fibers are gaining attention for their availability, mechanical strength, and eco-friendliness. These fibers not only reduce environmental impact but also provide adequate reinforcement properties when embedded in polymer matrices, making them suitable for semi-structural and even some structural applications [1]. Banana fibers, extracted from the pseudo-stem of banana plants, are typically considered agricultural waste, yet they exhibit high tensile strength and stiffness. Linen fibers, derived from the flax plant, are well-known for their exceptional mechanical performance and dimensional stability. These characteristics make both fibers viable candidates for reinforcement in composite laminates. When used in combination, as hybrid composites, the strengths of each fiber type can complement one another, potentially improving the overall performance of the composite. Hybridization allows designers to tailor materials for specific applications by optimizing mechanical behavior and moisture resistance.

Despite the potential benefits, one of the major concerns with NFRCs—particularly in high-performance sectors like aerospace and automotive—is their sensitivity to environmental conditions. Exposure to high humidity, fluctuating temperatures, and moisture absorption can deteriorate mechanical properties over time. The performance of hybrid composites under such adverse conditions remains underexplored, especially for banana-linen combinations. Understanding how these natural fibers behave in both isolated and combined states under stress is essential for expanding their application scope.

This research addresses this critical knowledge gap by systematically analyzing the mechanical performance of banana and linen fiber-reinforced composites under simulated extreme conditions. Laminates are fabricated using standard hand lay-up or compression molding techniques with varying fiber volume fractions. The specimens are then subjected to mechanical testing, including tensile strength, flexural strength, impact resistance, and moisture absorption, all of which are key indicators of structural integrity in real-world applications.

To enhance the efficiency and depth of this study, machine learning (ML) techniques are integrated into the research methodology. Specifically, the Random Forest algorithm is employed for predictive modeling. This ensemble-based learning algorithm is known for its high accuracy and ability to handle nonlinear relationships among multiple variables. By training the model using empirical data collected from the mechanical tests, the Random Forest algorithm can predict composite behavior based on parameters such as temperature, moisture content, and fiber composition. This predictive capability not only reduces the number of physical tests needed but also supports accelerated material development cycles, a significant advantage in industrial applications [2, 3].

The overall methodology follows a two-phase approach. In the experimental phase, composite laminates are fabricated, conditioned, and tested according to ASTM standards. Environmental conditioning chambers are used to simulate harsh service environments such as high-humidity conditions and elevated temperatures. The resulting data—comprising stress-strain curves, absorption rates, and failure modes—are collected and processed for ML analysis.

During the machine learning stage, the refined data are utilized to train and evaluate the Random Forest model. An analysis of feature importance is conducted to identify the variables that have the greatest impact on performance. This not only aids in the design of optimized composites but also helps prioritize material selection criteria for specific use cases [4, 5].

To contextualize this approach, previous studies have shown the efficacy of ML techniques in materials science. For instance, Li et al. [6] used the YOLO convolutional neural network architecture for damage detection in aircraft composite materials, demonstrating reliable results in real-time environments. Chen et al. [7] explored the integration of recurrent and convolutional neural networks to detect defects in 3D-printed composites, while Wang et al. [8] successfully applied artificial neural networks to study CFRP tubes under axial compression. These efforts reinforce the growing credibility of ML in material characterization and optimization.

 

Furthermore, earlier research has confirmed that both banana and linen fibers can individually enhance composite performance. Studies [9, 10, 11] report improvements in tensile and flexural properties, while hybridization has shown synergies in terms of mechanical stability and durability. This study extends such work by not only examining hybrid composites under harsh conditions but also integrating machine learning for predictive insights, thus creating a multi-disciplinary framework that merges material science with data-driven modeling.

In conclusion, this research contributes significantly to the sustainable engineering domain by demonstrating that eco-friendly composites can be both performance-driven and environmentally conscious. The integration of experimental methods with machine learning enhances the efficiency, reliability, and applicability of natural fiber composites, paving the way for their broader adoption in industries committed to green innovation and sustainable development.

## FABRICATION

### Prepare Fiber Layers

The Figure 1 shows the layup of banana and linen fiber sheets on a flat surface, ensuring that the layers are oriented in the required direction. The number of layers is determined by the desired thickness and the mechanical properties required for the composite laminate. Laminates consisting of six layers were manufactured with varying compositions of linen, banana, and their hybrid fabrics.

### Resin Impregnation

Epoxy resin Lapox L-12 is prepared. The resin is mixed with a hardener K-6 The resin is applied to the fiber layers using a brush.

### Layering the Composite

The banana and linen are stacked in alternating layers. The number of layers used is six in total

### Mold Preparation

The composite lay-up is placed in a mold. The mold is made of wood. Make sure the mold is thoroughly cleaned and correctly prepared before starting the composite lay-up. Breather fabric is placed over the laminate to prevent resin from sticking to the surface, making it easier to remove the vacuum bag after curing. A release film is used to facilitate easy removal of the laminate from the mold.

### Vacuum Bagging Setup

The entire lay-up is enclosed in a vacuum bag, a flexible airtight plastic film. The vacuum bag is sealed at the edges to ensure there are no leaks. A vacuum port is attached to the bag to allow the removal of air . Figures 2 and Figure 3 show the preparation of fibre layers and the layering of composite laminates.

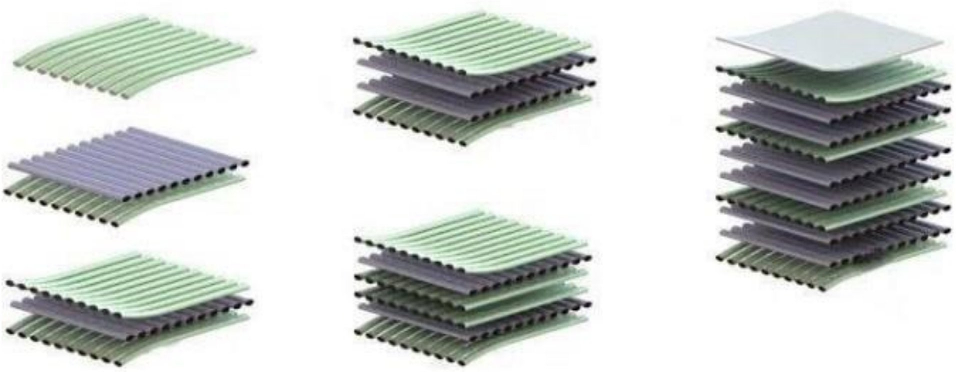

**Figure 1.** Layup fabrication process.

**Figure 2.** Preparing fiber layers.

**Figure 3.** Layering the composite laminate.

To ensure consistency and repeatability, the fiber volume fraction was carefully controlled during laminate fabrication by pre-weighing both fibers and resin before lay-up. The desired fiber-to-resin ratio was maintained by calculating the resin uptake for each type of fiber, considering their intrinsic absorbency characteristics. Laminates were fabricated using hand lay-up and vacuum bagging, which allowed excess resin to be extracted and reduced variability due to over-saturation. Verification of fiber volume fraction was done using ASTM D3171, Method II, through matrix burn-off in a muffle furnace to calculate voids and confirm fiber content. Following curing and trimming, specimens were subjected to simulated adverse environmental conditions. Laminates were conditioned in programmable environmental chambers set at temperatures ranging from –20°C (freezer simulation) to +100°C (oven exposure). Relative humidity was controlled at 85% RH during the high-moisture conditioning phase for 48 hours, simulating real-world service conditions like tropical and marine environments. These conditions were selected based on aerospace and automotive environmental exposure standards, ensuring that test results reflected practical applicability.

## TESTING PROCESS

### Post-Curing

- After the curing process, the laminate is removed from the mold and the vacuum bag.
- Trimming and finishing processes, such as sanding or cutting, are done to achieve the final dimensions and smooth surface.

### Adverse condition application

- After trimming and finishing the laminate, placing the laminates under adverse conditions i.e. in a freezer and in a hot oven.

### Mechanical Testing

The hybrid composite laminates made from banana and linen and their hybrid laminate fibers should undergo testing to evaluate their tensile strength after adverse condition application.

## DATASET PREPARATION

Given the limited number of experimental data points (Table 1), steps were taken to ensure the Random Forest model's robustness. Instead of solely relying on raw experimental points, interpolation and minor perturbation techniques were employed to synthetically augment the dataset without distorting underlying trends. Additionally, 5-fold cross-validation was implemented to mitigate overfitting and enhance generalizability. This approach provided a more reliable predictive framework, especially for exploring performance under conditions not directly tested. To train and validate the Random Forest model, a dataset was created based on realistic ranges for the input

 

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parameters. These values were selected to represent the expected operating conditions for banana-linen hybrid composites. The dataset includes the following ranges for the input variables:

- *Temperature (°C):* 25°C to 100°C
- *Fiber Volume Fraction (%):* 10% to 50%
- *Moisture Content (%):* 2% to 20%

The corresponding tensile strength (MPa) values were derived to reflect the material's behavior under these conditions. Below is an example of the dataset used for training and testing (Table 1).

**Machine Learning Methodology: Application of Random Forest Regression**

***Rationale for Choosing Random Forest***

Random Forest regression was chosen for this study owing to its flexibility and strong performance, especially with limited datasets. It excels at capturing intricate relationships between input features and output responses. By aggregating the results of multiple decision trees, Random Forest minimizes variance and improves model generalization, thereby reducing the risk of overfitting. Additionally, it provides a straightforward evaluation of feature importance, allowing us to determine the key variables influencing the outcomes of the analysis Feature importance analysis performed on the trained Random Forest model revealed that fiber volume fraction was the most influential parameter affecting tensile strength, followed by moisture content and temperature, in that order. This ranking aligns with the physical behavior of natural fiber composites, where fiber content directly affects load-carrying capacity, and moisture significantly deteriorates interfacial bonding, reducing strength. Temperature had a secondary effect, primarily influencing resin ductility and thermal degradation of fibers

**Key Input Variables**

Three primary factors were analyzed to determine their impact on tensile strength: Temperature (°C): Investigates how thermal variations influence material properties.

1. *Fiber Volume Fraction (%):* Represents the ratio of fiber to other materials in the composite.
2. *Moisture Content (%):* Assesses the effect of water absorption on the material's structural integrity.
3. *Target Output:* Tensile Strength (MPa).

Tensile strength is an essential indicator of a material's ability to withstand breaking when subjected to tension. Accurate prediction of this property is essential for evaluating the composite's suitability for demanding applications, especially in challenging environments.

**Model Development and Validation**

A dataset was constructed using experimentally derived values for temperature, fiber volume fraction, and moisture content. The Random Forest Regressor was implemented with carefully tuned parameters to optimize predictive accuracy. The dataset was partitioned into training (80%) and testing (20%) subsets to evaluate the model's performance. The predictive accuracy was evaluated using metrics like Mean Squared Error (MSE) and R-squared ($R^2$), ensuring the model's dependability and accuracy. The sample data set for tensile test vs predicted is shown in the Figure 4.

**Table 1.** Dataset used for the analysis.

| Temperature (ºC) | Fiber volume fraction (%) | Moisture content (%) | Tensile strength (MPa) |
|---|---|---|---|
| 25 | 10 | 2 | 45.3 |
| 50 | 20 | 5 | 38.7 |
| 75 | 30 | 10 | 32.4 |
| 100 | 40 | 15 | 28.1 |
| 25 | 50 | 20 | 22.5 |

 

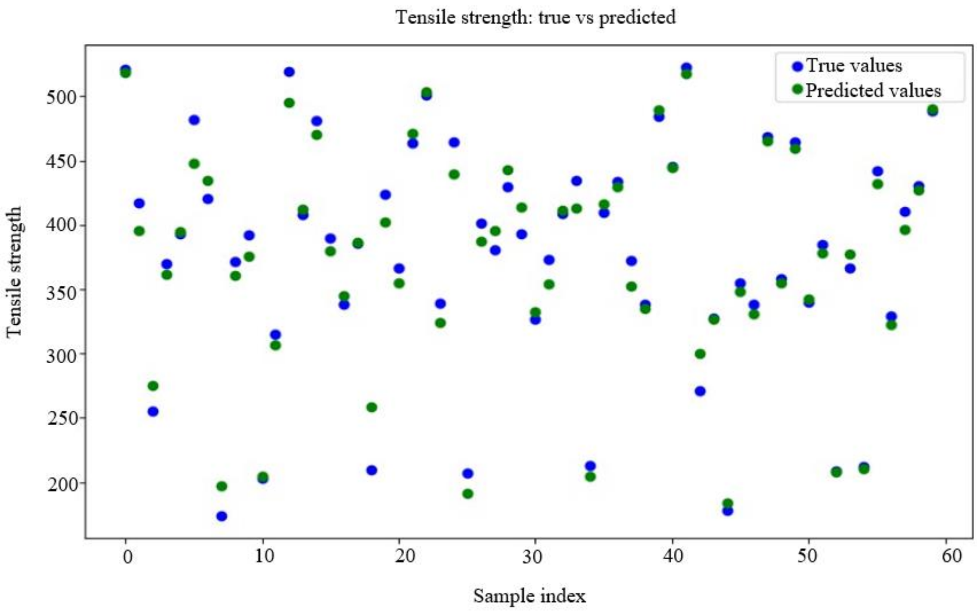


**Figure 4.** Sample Output

## CONCLUSION

This study investigated the mechanical properties of banana, linen, and hybrid-reinforced composite laminates under challenging conditions, with an emphasis on tensile strength, flexural strength, impact resistance, and moisture absorption. The results revealed that hybrid composites combining banana and linen fibers exhibit superior mechanical performance compared to pure fiber composites, demonstrating the benefits of hybridization. The integration of the Random Forest algorithm enabled accurate predictions of material behavior, reducing reliance on extensive physical testing and providing a framework for optimizing composite designs.

The findings underscore the potential of banana-linen hybrid composites as sustainable alternatives for industries like aerospace and automotive, where materials face harsh environmental conditions. The use of machine learning, particularly Random Forest, offers a promising approach to accelerate material development and optimization.For future work, additional testing under varied conditions, such as dynamic loading and prolonged exposure to extreme temperatures, is recommended. Expanding the dataset and exploring advanced ML techniques could further enhance predictive accuracy. Investigating the incorporation of other natural fibers or nanomaterials into hybrid composites may also improve mechanical properties and environmental resistance.

Finally, developing cost-effective manufacturing processes and assessing ecological impacts will be crucial for broader industrial adoption. In conclusion, this research advances the understanding of sustainable materials by combining experimental and computational approaches, paving the way for eco-friendly composite innovations. In addition to short-term mechanical testing, long-term durability assessments are planned to validate ML model predictions under extended environmental exposure and fatigue loading. Future work will include accelerated aging, UV exposure, and cyclic loading tests to assess creep and fatigue performance over time. These studies will not only validate ML models in real-world conditions but also provide deeper insight into the time-dependent degradation of natural fiber composites.

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