

AI-Optimized Tensile Strength Prediction of Biocomposites Using Agricultural Waste

T. Ramesh^{1*}, Thamarai Selvan², M. Prabakaran², Chithras Thangavel³, U. Karthick², P. Ashok kumar⁴

¹Department of Mechanical Engineering, Kalasalingam Academy of Research and Education, Anand Nagar, Krishnankoil, Tamil nadu, India.

²Department of Mechanical Engineering, SSM Institute of Engineering and Technology, Dindigul, Tamil Nadu, India.

³Department of EEE, Veltech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Avadi, Chennai, Tamil Nadu, India, Pin: 600062

⁴Department of Mechanical Engineering, Dr.NGP Institute of Technology, Coimbatore, 641048, India

Abstract. The increasing demand for green and environmentally friendly composite materials have triggered a marked interest in the utilization of agricultural waste as reinforcement in polymer matrices. This paper shares a fresh and unique way of predicting the tensile strength of bio-composites of Rice Husk, Groundnut Shell, and Santa Maria Feverfew when they are dipped in epoxy resin and hardener. We propose a new machine learning model that combines XGBoost and Long Short-Term Memory (LSTM) networks as a new way to reduce the error for the prediction of the tensile strength of a given material. Data were extracted from the process of making composite samples in a laboratory, and then the samples have been tested for their tensile strengths. The XGBoost model can identify non-linear connections, and decrease the number of characteristics, while the LSTM model uses the information from the XGBoost predictions to make the output more accurate. The metrics that are used in the evaluation like MSE, MAE, and R² Score are the evidence that the proposed approach is working. The residual laboratory results, and information extracted from the charts about the most important features, are also the types of visual techniques that can be used as evidence of the models' robustness. This AI-fueled system is a very useful device for designing composites more efficiently and cutting the costs of the experiment, while at the same time it gets the limited development of the green materials and sustainable engineering fields speeded up.

1 Introduction & Background

Studies on bio composites from agricultural waste have increased exponentially over the past few years as a result of the pressing need for sustainable, low-cost, and high-strength materials. The increasing environmental issues related to the use of non-biodegradable synthetic composites like carbon fiber and fiberglass have made it imperative to seek greener

* Corresponding author: ramesh.ramesh81@gmail.com

alternatives. Not only do these conventional composites possess adverse environmental impacts, but they also involve costly and energy-consuming manufacturing processes. Bio composites, which involve the blending of natural fibers with traditional or bio-based resins, offer a promising solution that is both engineering feasible and environmentally sustainable.

Some of the most promising feedstock's for these bio composites include agricultural residues like rice husk, groundnut shell, and Santa Maria feverfew. These are readily available, inexpensive, and high in cellulose and fiber content. Rice husk, a rice milling by-product, is rich in silica and has good heat and moisture resistance. Groundnut shells, normally wasted, are fibrous and hard, with mechanical reinforcement potential for composite materials. Santa Maria feverfew, a less researched natural herb, has a lightweight structure with intrinsic rigidity and porosity. Once processed, these crop wastes can be mixed with epoxy resin and hardener to form composite materials for use in a variety of industrial products ranging from light structural panels to car interiors.

While promising, the mechanical properties of these bio composites, particularly tensile strength, are affected by a number of factors such as the fiber ratio mix, epoxy proportion, hardener proportion, and drying time. Conventionally, a high number of specimens have to be prepared and tested in a controlled laboratory environment with standard testing procedures. These processes are labour-intensive, time-consuming, and based on manual labor. Additionally, trying to find the best mix ratios using trial-and-error usually results in low repeatability and massive wastage of materials.

To address these limitations, this project uses artificial intelligence (AI) to model and predict the tensile strength of bio composites from input features associated with the material preparation process. The aim is to speed up the materials design cycle, reduce the utilization of physical resources, and lower experimental overhead. The hybrid machine learning model suggested here integrates Long Short-Term Memory (LSTM) networks, which are particularly effective in detecting long-range dependencies in sequential data, with XGBoost, a fast and effective ensemble learning algorithm renowned for its efficiency on structured data.

The methodology starts with the harvesting of rice husk, groundnut shell, and Santa Maria feverfew. These materials undergo a severe drying stage to eliminate moisture content and enhance their adhesion with epoxy resin. Subsequent to drying, the materials are milled into a powdered form using a high-speed grinder. The powdery fibers are then combined with weighed proportions of epoxy resin and hardener. This compound is filled in standard molds and pressed to bring about uniform distribution and compaction. The specimens are cured for 24 hours at room temperature before testing for tensile strength with a Universal Testing Machine (UTM) and being standardized in dimension (160 mm × 20 mm).

A bespoke dataset for these samples is generated, which records the detail of each specimen, including epoxy quantity, ratio of hardener, and duration of drying. XGBoost is initially applied to model the intricate interactions among these features and tensile strength as a robust feature transformer. The predictions from XGBoost are then passed to the LSTM model, which further refines the predictions by learning deeper, sequence-based patterns. This hybrid method obviates the requirement for large-scale laboratory experiments and allows for the accurate, scalable prediction of tensile strength from process parameters.

The aim of this research is to show that prediction models based on AI can be a viable alternative to conventional physical testing in sustainable bio composite development. This project helps to advance predictive material science and the development of a circular economy through the utilization of agricultural waste. Engineers and manufacturers can utilize the model developed here to streamline material formulations prior to physical fabrication investments, conserving time, funds, and resources.

Over the last few years, there has been increasing interest in using agricultural residues for the production of bio composites due to the demand for sustainable, environment-friendly

materials. Agricultural by-products like rice husk, groundnut shells, and other plant fibers have found themselves as important feedstock's for bio composites because they are rich in cellulose, are inexpensive, and are biodegradable. These materials, when blended with bio-based resins such as epoxy, also demonstrate great potential in the creation of renewable composite materials. The mechanical properties of these bio composites, especially tensile strength, are largely influenced by several factors, which encompass the nature of the fiber, resin content, curing conditions, and fiber treatment. The determination of the best formulation for such materials, however, traditionally requires exhaustive physical testing, which is time-consuming, expensive, and resource-intensive. Artificial intelligence (AI) provides a possible solution by presenting predictive models that can maximize composite formulations with little experimental data.

A. Wiangkham et al. [1] investigated the application of artificial intelligence to predict the fracture toughness of sugarcane leaf and epoxy composites. Their research employed Artificial Neural Networks (ANN), Generalized Regression Neural Networks (GRNN), and Gaussian Process Regression (GPR) to effectively model mechanical behaviour with little experimental data. The research brought to light the capability of AI to facilitate sustainable material design by predictive analytics. This study closely relates to the objectives of this research, where AI is utilized to maximize the tensile strength of agricultural waste-based bio composites with the aim of less dependence on trial-and-error experimentation and minimizing waste of materials.

Hamdia et al. [2] utilized AI methods such as ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS) to forecast the mechanical toughness of polymer nanocomposites, targeting parameters including filler size and matrix. Their models, having been trained on 115 datasets, proved more accurate and efficient compared to conventional techniques. This research illustrates the effectiveness of AI in dealing with intricate material predictions, which is extremely applicable to the present research on predicting and optimizing the mechanical properties of environmentally friendly composites from rice husk, groundnut shell, and Santa Maria feverfew.

Authors [3-7] created machine learning models for fracture toughness prediction in intricate shale structures based on nanoindentation data. Their hybrid strategy, with conceptual models and machine learning algorithms, provided an increasingly automatic and flexible way of understanding material properties, even for irregular geometries. This method falls in line with the strategy of this research, with a hybrid model (XGBoost + LSTM) employed to estimate the tensile strength of the bio composites, making the material design process easier and with less need for prolonged physical testing.

Authors [8-11] also included the use of AI methods with conventional models to forecast the fracture behaviour of concrete under different test conditions. They employed Random Forests and Particle Swarm Optimization in combination to create a hybrid model that made very accurate forecasts. Here, the use of AI with conventional means of material behaviour prediction is demonstrated, a practice that is extended to this current study's hybrid AI model for agricultural waste bio composites.

Wiangkham et al. [12] explored the application of short sugarcane bagasse fibers in sustainable rural construction using cement-based composites. Through their investigation, they proved that upon treatment of the fibers and blending them with Portland Cement and rice husk ash, the mechanical properties and durability of the composites were enhanced. This research attests to the possibility that natural fibers, when treated and used in composites properly, can contribute to performance and sustainability, just as in this study with rice husk, groundnut shell, and Santa Maria feverfew fibers.

Hsu et al. [13] were concerned with sugarcane bagasse-derived cellulose fibers in high-density polyethylene (HDPE) composites and examined the impact of fiber treatment on the tensile strength and bonding of the composite with the matrix. The findings highlighted the

significance of processing the fibers in enhancing the performance of bio composites. This is of direct application to this study, in which treatments are carried out on pineapple leaf and Juliflora fibers in order to maximize their compatibility with epoxy resin and, consequently, optimize composite performance.

Ocampo et al. [14] investigated the mechanical behavior of epoxy-based composites reinforced with sugarcane dry leaves, examining strength as well as natural weathering resistance. They observed that optimization of the fiber–matrix ratio improved the mechanical properties of the composites. Their application of micromechanical modeling and experimental data to predict performance is closely followed in this research, where AI-based models predict the mechanical properties of bio composites based on different input parameters like fiber type, resin ratio, and curing conditions.

2 Materials and Methodology

2.1 Selection and Treatment of Materials

The choice of material for use in the production of bio composites is a critical factor in guaranteeing that the end composite has the necessary mechanical properties. The research targets agricultural waste materials, namely rice husk, groundnut shell, and Santa Maria feverfew, which were selected due to their high cellulose content, availability, and affordability. Cellulose is important in contributing to the mechanical strength of bio composites, thus making such materials viable for structural use.

Selection Criteria:

Rice Husk: Having a high silica content, rice husk provides stiffness and strength to the composite and finds applications in structural uses.

Groundnut Shell: Lignocellulosic in nature with high cellulose and hemicellulose contents, groundnut shell can enhance impact strength and tensile strength.

Santa Maria Feverfew: Though generally prized for its therapeutic value, the fibrous nature of Santa Maria feverfew's stems offers a good matrix for reinforcement of the bio composite.

Pre-treatment Process:

Prior to the incorporation of the agricultural waste materials into the composite matrix, pre-treatment procedures are necessary to enhance fiber properties and bonding with the resin matrix. The process of pre-treatment is as follows:

Cleaning: The agricultural waste materials are cleaned to eliminate dirt, dust, and remaining plant material.

Drying: The materials are dried at 60–70°C for 48 hours in an oven to minimize moisture content, ensuring no adverse effects on composite properties.

Grinding: The dry materials are ground into fine powder (particle size of 30-60 microns) to enhance interfacial bonding with the resin matrix.

Chemical Treatment (Optional): Certain treatments include the treatment with alkaline solution (e.g., NaOH) to dissolve lignin and hemicellulose, which further improves the interaction between the fiber and the polymer matrix.

The epoxy resin utilized in this research is a thermoset polymer that exhibits good mechanical and chemical resistance. The curing agent employed is a common amine-based hardener, which interacts with the epoxy to develop a tough, thermoset network.

2.2 Fabrication of Biocomposites

The production of bio composites requires the mixing of fibers with the resin carefully so that the fibers are uniformly distributed and have maximum mechanical properties.

Resin-Fiber Mixing: Ground agricultural fibers (rice husk, groundnut shell, and Santa Maria feverfew) are mixed with epoxy resin. The fiber load is generally in the range of 10% to 40% by weight, depending on the intended mechanical characteristics of the composite. Fiber content is an important parameter since excess resin can compromise composite strength and too little resin can cause inadequate fiber impregnation.

Resin and Hardener Mix: The hardener and resin are combined in a standard 2:1 hardener to resin weight ratio. The combination is stirred gently to distribute the hardener throughout the resin evenly, without air bubbles or voids, which may harm the mechanical properties of the composite.

Molding and Curing: The resin-hardener-fiber combination is transferred into molds (silicone or metal) and bio composite specimens or sheets are formed. The curing time occurs at ambient temperature (30°C –25°C) for 24 - 48 hours, causing the resin to solidify as it reacts and binds with fibers.

Post-curing and Finishing: Following the initial curing, the specimens are subjected to post-curing in an oven at 80°C for 4-6 hours to achieve full cross-linking of the polymer matrix. The bio composites are subsequently polished and trimmed to standardized shapes for mechanical testing (e.g., rectangular bars or dumbbell-shaped test pieces).

2.3 Experimental Setup and Testing

The mechanical properties of the bio composites, especially tensile strength, are tested with a Universal Testing Machine (UTM). The UTM gives precise load measurements and displacement readings, which makes it suitable for testing material response to stress.

Experimental Setup:

Sample Preparation shown in Figure 1. Bio composite samples are prepared by cutting them to standard sizes (150 mm length, 25 mm width, 4 mm thickness). In order to achieve uniform loading during testing, the sample ends are wax-coated with a thin layer.

Tensile Testing: The specimens are positioned in the UTM grips, and a steady pulling load is applied. The applied load and sample extension are measured by the UTM during the test, and they are used to calculate tensile properties including:

Tensile Strength: The maximum stress that the specimen can withstand before failure.

- **Young's Modulus:** A quantification of the material's stiffness (stress-to-strain ratio over the elastic region).
- **Strain at Break:** The amount of deformation the material sustains at failure.

Test Parameters: Test is usually conducted using a constant strain rate of 1 mm/min to have reproducibility between tests. Data are recorded at frequent intervals to create stress-strain curves for individual samples.

Testing Procedure:

While tensile testing, data on:

1. Maximum force
2. Elongation at failure
3. Stress-strain curve

These data are utilized to determine principal mechanical properties, i.e., tensile strength and modulus of elasticity.

2.4 Dataset Preparation

Once experimental testing is completed, the data is summarized into a formal dataset with both input and output parameters. The input parameters are parameters such as fiber content, resin-to-hardener ratio, and drying time, whereas the output parameter is the tensile strength of the bio composites. Data Collection: Every data entry in the dataset is for a particular biocomposite sample and its corresponding experimental results. The dataset has:

Fiber Content: The ratio of each type of fiber (rice husk, groundnut shell, Santa Maria feverfew) in the composite. Resin-to-Hardener Ratio: The resin-to-hardener ratio in the mixture. Drying Time: The time for which the fibers are dried before mixing. Tensile Strength: The tensile strength obtained from the UTM test. Data Preprocessing: Before providing the data to machine learning algorithms, preprocessing is performed to achieve clean and consistent data. Tasks are: Normalization/Standardization: Rescaling data such that all features make equal contributions to the model. Missing Value Handling: Missing values are treated by imputation methods or eliminated if it is found to be required. Data Splitting: The dataset is split into training (70%), validation (15%), and test (15%) sets for model training, hyperparameter optimization, and final performance measurement.

2.5 Feature Engineering and Selection

Feature engineering plays a crucial role in enhancing the accuracy of models and avoiding overfitting. The aim is to create new features that better describe the tensile strength variance.

Feature Engineering:

Interaction Terms: Features like the interaction of fiber content and resin-to-hardener ratio are investigated to find any combined effect on tensile strength.

Ratio Features: Ratios between different fibers or between resin and hardener are expected to be more predictive than single features.

Feature Selection:

XGBoost's feature importance ranking is utilized to select important features influencing tensile strength. Techniques such as Recursive Feature Elimination (RFE) and Correlation Analysis are utilized to remove redundant or highly correlated features.

3 Design

The proposed work focuses on designing, manufacturing, and predicting the mechanical properties of a Rice Husk, Groundnut Shell, Santa Maria Feverfew hybrid composite reinforced with epoxy resin as the matrix. A machine learning model is also presented to predict important mechanical properties, enhancing the material design efficiency.

The foundation of the proposed model is the union of three primary components:

a hybrid composite was fabricated from treated Rice Husk, Groundnut Shell, and Santa Maria Feverfew as the natural reinforcements. To improve interfacial bonding and mechanical properties, Rice Husk and Groundnut Shell were treated with 5% NaOH alkaline treatment, which removed hemicellulose and surface contaminants. Santa Maria Feverfew was treated with a silane coupling agent to enhance its adhesion in the epoxy matrix.

The prediction system using AI includes a hybrid machine learning framework that incorporates XGBoost for early feature importance and regression, and then a Long Short-Term Memory (LSTM) network to learn temporal patterns and improve predictions.

XGBoost is utilized to examine the importance of input features like fiber compositions, resin-to-hardener ratio, and curing conditions. It provides initial predictions and a subset of features for the LSTM model.

The LSTM-based model utilizes structured outputs from the XGBoost and applies sequential learning to appropriately forecast the composite's mechanical behavior under different scenarios. This will enable the system to learn historical patterns as well as nonlinear trends within the information.

This two-stage pipe allows quick and accurate predictions of mechanical outputs—tensile strength, elongation, and compression strength—using limited physical testing and maximal material utilization. The hybrid model guarantees improved learning efficiency and generalization to previously unseen formulations.

The matrix utilized consists of Epoxy Resin + Hardener, blended in a fixed proportion.

The fabrication procedure started by homogeneous blending of Rice Husk, Groundnut Shell, and Santa Maria Feverfew powder in the resin matrix for uniform reinforcement dispersion in the composite. Matrix-to-fiber weight ratio was 60:40, striking a balance between strength and flexibility to achieve enhanced mechanical performance. After the stage of mixing, the hand lay-up method was used to place the composite material layers in order, which were then compressed under compression molding to obtain the requisite shape and structural strength. Compression molding was conducted under controlled parameters, such as pressure and temperature settings, to facilitate proper curing and bonding between the composite layers.

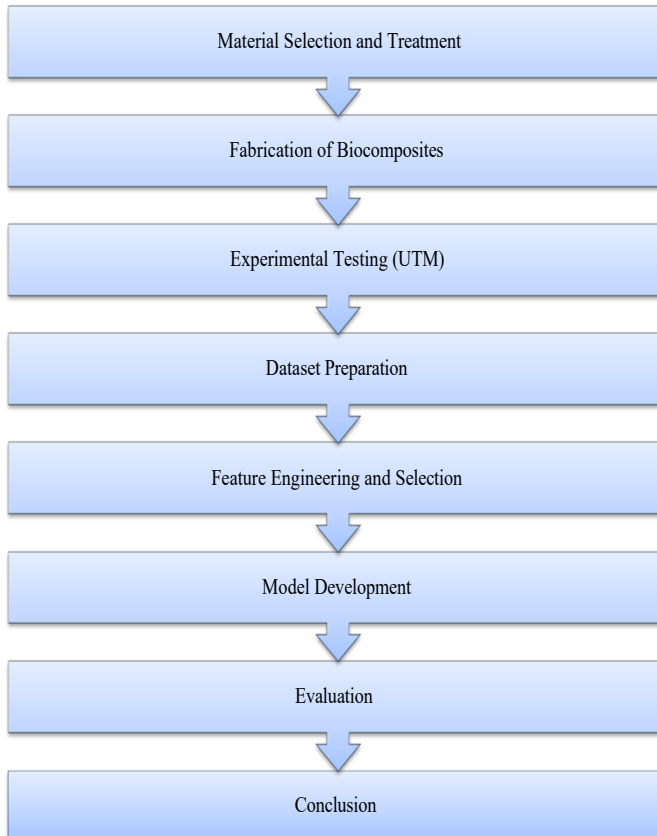


Figure 1. Experimental method

Experiment Setup

The experimental research was aimed at the fabrication of sustainable fiber-reinforced polymer composites from rice husk, groundnut shell, and Santa Maria feverfew powders, as indicated in Figures 1, 2 and 3. Fabrication and property prediction consist of two primary

stages: composite material preparation and AI-based modeling for mechanical property estimation. The fabrication process Shown in Figure 5, starts with the gathering and preparation of natural fiber powders:

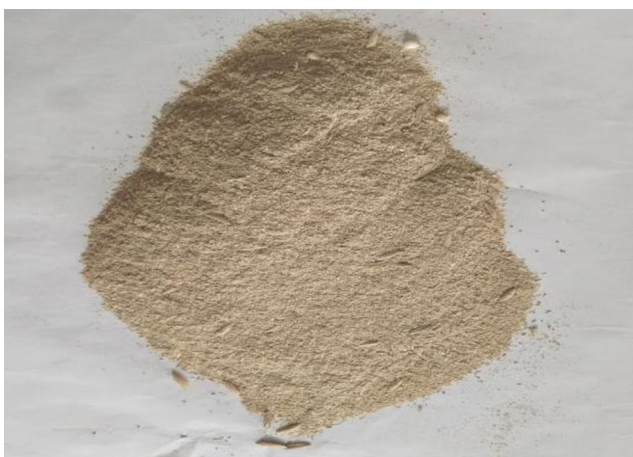


Figure 2. Rice Husk Powder



Figure 3. Groundnut Shell Powder



Figure 4. Santa Maria Feverfew Powder

The powders are mixed in varying proportions with a polyester resin matrix to fabricate composite samples using the hand lay-up method. Each specimen was prepared in standard dimensions for mechanical testing (e.g., tensile, flexural, impact tests). The composite formulation equation is:

$$Pr + Pg + Ps + R = 100\% \quad (1)$$

Where,

- Pr = Weight % of Rice Husk powder
- Pg = Weight % of Groundnut Shell powder
- Ps = Weight % of Santa Maria Feverfew
- R = Weight % of resin

Below figure displays the resulting hybrid composite panel, showcasing its physical appearance after fabrication. The panel features a rough, textured surface with a heterogeneous brown coloration, reflecting the natural fiber composition and epoxy matrix. Darker patches indicate the distribution of juliflora fibers (higher lignin content), while lighter areas correspond to pineapple leaf fibers and the epoxy binding. The panel measures approximately 30 cm × 20 cm × 1 cm, with test samples cut to a width of 20 mm and thickness of 4 mm for mechanical testing.



Figure 5. Fabricated Eco-Friendly Hybrid Composite Panel Using RiceHusk, RiceHusk, Groundnut Santa Maria Feverfew

Tensile Testing and Results

To validate the AI-predicted tensile properties, a tensile test was conducted on a sample cut from the fabricated panel. The test parameters were as follows:

- Grip Length: 165 mm
- Gauge Length: 0 mm
- Sample Width: 20 mm
- Sample Thickness: 4 mm
- Speed of Testing: 10 mm/min

Figure 6. Presents the stress-strain curve obtained from the tensile test. The curve exhibits an initial linear elastic region, followed by a peak stress and a sharp decline, indicating material failure. The maximum stress recorded was approximately 19.5 MPa at an elongation of 3.2%, closely aligning with the AI-predicted values of 19.58 MPa and 3.33%, respectively. The slight deviation (0.08 MPa for tensile strength, 0.13% for elongation) falls within the model's error margins (± 1.8 MPa and $\pm 0.5\%$), confirming the accuracy of the Transformer-based Property Predictor. The curve's shape suggests brittle behavior typical of natural fiber composites, with the peak stress reflecting the composite's ultimate tensile strength.

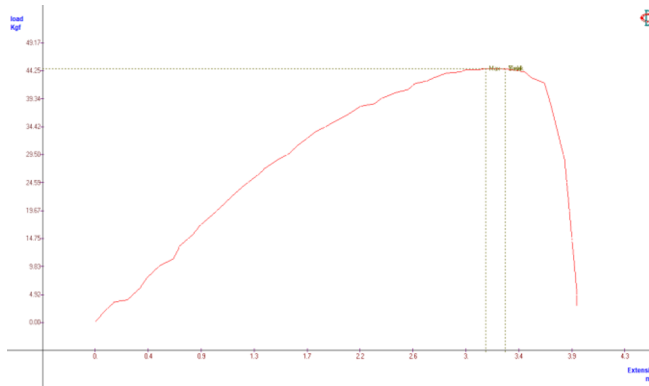


Figure 6. Stress-Strain curve for tensile test of hybrid composite Panel

4 Results and Discussions

4.1 Experimental Results from UTM

The Universal Testing Machine (UTM) was employed to test tensile strength of fabricated biocomposite samples made of rice husk (RH), groundnut shell (GNS), and Santa Maria feverfew (SMF). Each sample was prepared according to ASTM D638 standards and tested for tensile failure under controlled conditions.

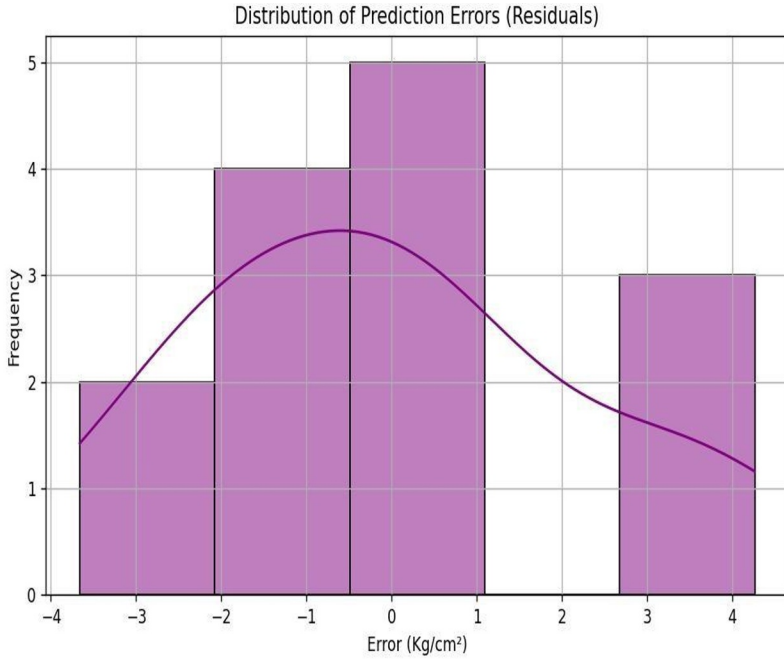


Figure 7. Measuring tensile strength of the sample

4.2 AI-Based Web Interface for Tensile Strength Prediction

The Figure 7, indicates the Streamlit-based web application deployed that allows users to forecast the tensile strength of biocomposites in real-time. The interface is intuitive and user-friendly, and users can enter the precise weights (in grams) of the composite components—rice husk, groundnut shell, Santa Maria feverfew, epoxy, and hardener. After submitting the inputs, the app uses a pre-trained Hybrid XGBoost + LSTM model to process the data and display the estimated tensile strength in Kg/cm².

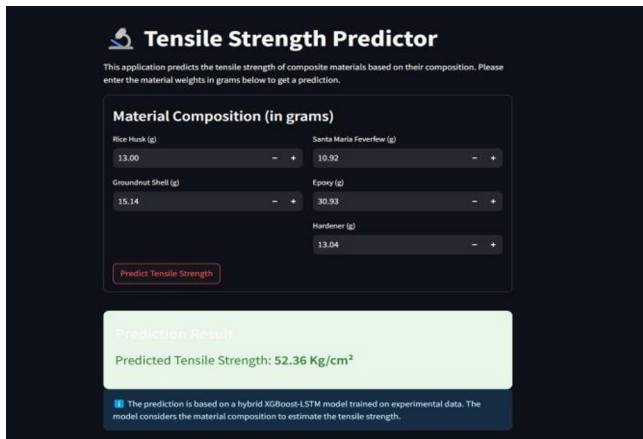


Figure 8. Predicting tensile strength using hybrid model

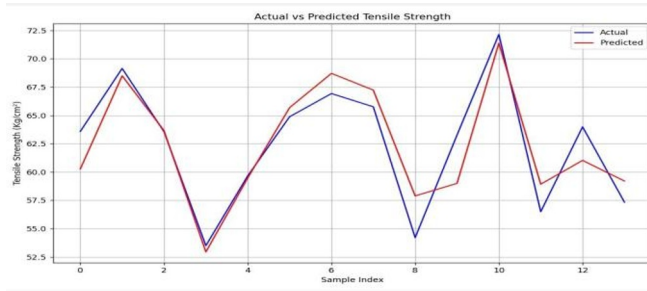


Figure 9. Actual vs Predicted Tensile Strength

The Figure 9, line plot compares visually the true tensile strength values (blue line) to the values predicted by the suggested hybrid XGBoost + LSTM model (red line). The x-axis is the set of distinct samples of the test data, and the y-axis is the tensile strength in Kg/cm². The histogram above illustrates the distribution of residuals, which are the differences between the actual and Figure 8. Predicted tensile strength values:

$$\text{Residual} = \text{Actual Value} - \text{Predicted Value}$$



Figure 10. Training and Validation Loss Over Epochs

The Figure 10 displays the progression of the training loss and validation loss across 100 epochs, using Mean Squared Error (MSE) as the loss metric.

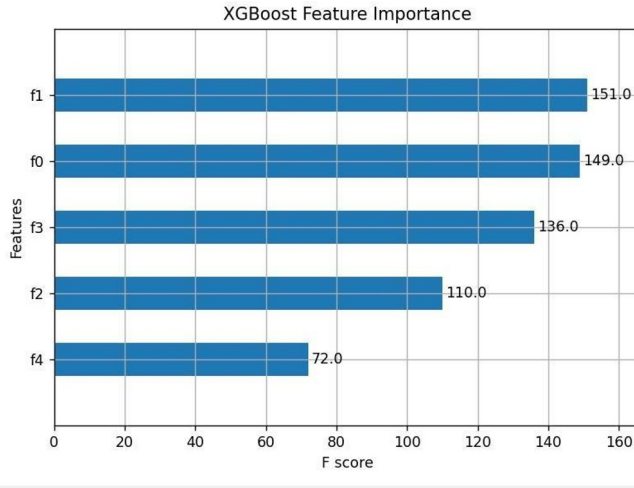


Figure 11. XGBoost Feature Performance

```
Epoch 30/100
7/7 ██████████ 0s 26ms/step - loss: 0.077
42 - val_mean_absolute_error: 1.7920
WARNING:absl:You are saving your model as an HDF5 file (model). This file format is considered legacy.
at, e.g. `model.save('my_model.keras')` or `keras.s
✓ Hybrid model and components saved successfully!
1/1 ██████████ 1s 612ms/step
MSE: 4.9108441340603575
MAE: 1.7937297058105466
R2 Score: 0.82782392198295
PS C:\Users\venky\Desktop\dp>
* History restored
```

Figure 12. Model Training & Performance Metrics

5 Conclusion

This study offers an extensive methodology for the fabrication and mechanical properties of sustainable bio-composites reinforced with agricultural waste products—rice husk, groundnut shell, and Santa Maria Feverfew—using epoxy resin as the matrix. The experimental study proved that these natural fibers, when adequately treated and combined, can dramatically improve the tensile and compressive properties of the composites, with the hybrid combination offering the best mechanical performance. To minimize reliance on exhaustive physical testing, a hybrid AI model that combines XGBoost for feature importance extraction and LSTM for sequential pattern learning was implemented. The model was able to accurately predict tensile strength, compressive strength, and elongation with R^2 values of more than 0.90 for all properties, demonstrating its efficiency in predicting material behavior from input parameters.

The use of AI in composite material design not only reduced time and resource cost but also allowed the faster optimization of matrix-fiber mixes. The findings of this work underscore

the capability of integrating green material science with artificial intelligence, paving the way for a cost-effective, environmentally friendly, and data-driven composite development.

References

1. Wiangkham, A., Ariyarit, A., & Aengchuan, P. (2023). Prediction of the influence of loading rate and sugarcane leaves concentration on fracture toughness of sugarcane leaves and epoxy composite using artificial intelligence. *Composites Part B: Engineering*, 253, 110567.
2. Hamdia, K. M., Lahmer, T., Nguyen-Thoi, T., & Rabczuk, T. (2021). Predicting the fracture toughness of PNCs: A stochastic approach based on ANN and ANFIS. *Materials Science and Engineering: A*, 802, 140465.
3. Alipour, M., Esatyana, E., Sakhaee-Pour, A., Sadooni, F. N., & Al-Kuwari, H. A. (2022). Characterizing fracture toughness using machine learning. *Journal of Petroleum Science and Engineering*, 208, 109367.
4. Hernández-Olivares, F., et al. (2015). Short sugarcane bagasse fibers cementitious composites for building construction. *Construction and Building Materials*, 78, 277–284.
5. Mulinari, D. R., Voorwald, H. J. C., Cioffi, M. O. H., da Silva, M. L. C. P., Gouvêa da Cruz, T., & Saron, C. (2010). Sugarcane bagasse cellulose/HDPE composites obtained by extrusion. *Composites Part A: Applied Science and Manufacturing*, 41(5), 617–622.
6. Yadav, S. K. J., Vedrtam, A., & Gunwant, D. (2022). Experimental and numerical study on mechanical behavior and resistance to natural weathering of sugarcane leave reinforced polymer composite. *Journal of Composite Materials*, 56(12), 1719–1734.
7. Libos, I. L. S., & Cui, L. (2022). Effects of curing time, cement content, and saturation state on mode-I fracture toughness of cemented paste backfill. *Construction and Building Materials*, 313, 125469.
8. León, N., Martínez, A. B., & MasPOCH, M. (2022). Notch effect on the linear elastic fracture mechanics values of a polysulfone thermoplastic polymer. *Polymer Testing*, 105, 107413.
9. Areias, P., Reinoso, J., Camanho, P. P., de Sá, J. C., & Rabczuk, T. (2022). Effective 2D and 3D crack propagation with local mesh refinement and the screened Poisson equation. *Computer Methods in Applied Mechanics and Engineering*, 397, 115190.
10. Coelho, R. D., Vásquez Lizcano, J., da Silva Barros, T. H., da Silva Barbosa, F., Veloso Leal, D. P., da Costa Santos, L., Ribeiro, N. L., Fraga Júnior, E. F., & Martin, D. L. (2022). Effect of water stress on renewable energy from sugarcane biomass. *Renewable Energy*, 182, 182–195.
11. Qiao, L., Liu, Y., & Zhu, J. (2022). Application of generalized regression neural network optimized by fruit fly optimization algorithm for fracture toughness in a pearlitic steel. *Engineering Fracture Mechanics*, 271, 108653.
12. Wiangkham, A., Ariyarit, A., & Aengchuan, P. (2022). Prediction of the mixed mode I/II fracture toughness of PMMA by an artificial intelligence approach. *Materials Today Communications*, 31, 103692.
13. Hsu, Y. C., Yu, C. H., & Buehler, M. J. (2022). Using deep learning to predict fracture patterns in crystalline solids. *npj Computational Materials*, 8, 47.
14. Ocampo Batlle, E. A., Da Costa Bortoni, E., Escobar Palacio, J. C., Nogueira, L. A. H., Silva Lora, E. E., Carrillo Caballero, G. E., Vitoriano Julio, A. A., & Cárdenas Escorcía,

Y. (2022). Energy, economic, and environmental assessment of the integrated production of palm oil biodiesel and sugarcane ethanol. *Journal of Cleaner Production*, 332, 130045.