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Application of Artificial Neural Network for Parameters Optimization on Tensile Properties via Hand Lay-up Techniques for Kenaf/Fibreglass Reinforced Hybrid Composite

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ABSTRACT

The growing demand for sustainable, high-performance materials has led to the development of hybrid composites that integrate natural and synthetic fibers. This study explores the tensile properties of kenaf/fiberglass reinforced polyester hybrid composites fabricated through the hand lay-up technique. Composites incorporating varying kenaf fiber weight percentages (15%, 45%, 60%, and 75%) were evaluated in accordance with American Society for Testing and Materials (ASTM) D3039 standards. Additionally, an Artificial Neural Network (ANN) model was constructed to predict tensile strength based on fiber content, composite thickness, and defect levels. The model was trained using three different algorithms: Levenberg-Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG). The composite with 45% kenaf fiber demonstrated the optimal tensile performance. The highest measured tensile strength reached 50.47 MPa. The ANN model achieved a high prediction accuracy with a correlation coefficient (R) of 0.9686 and a Mean Squared Error (MSE) of 0.0063. Among the training algorithms, the LM algorithm outperformed the others in terms of prediction accuracy. These findings highlight the effectiveness of ANN modelling in optimizing hybrid composite formulations, minimizing experimental requirements, and advancing their use in structural applications.

1. INTRODUCTION

Because of their remarkable qualities, composite materials are used extensively in a wide range of industrial applications, including the maritime, aviation, and civil infrastructure sectors. Because of their exceptional stiffness-to-weight ratio, high strength-to-weight ratio, and superior corrosion resistance, these materials are a great option for structural elements in a variety of sectors. Fiber-reinforced polymers, or FRPs, have therefore proliferated in these industries. Their exceptional durability, low weight, and adaptable mechanical qualities have made them essential in a variety of industries, including maritime engineering and aerospace [1]. Understanding the fatigue behaviours of composite materials has become crucial for engineering design considerations as their use in structural designs grows. Maintaining the dependability and functionality of components subjected to repeated loads over time requires materials that can tolerate long-term loading and cyclic stress. As a result, design engineering now prioritises maximising profit while maintaining customer comfort and safety [2].

Composite material production is dominated by synthetic fibres, which are mostly made by chemical synthesis from basic materials. These synthetic fibres are ideal for structural reinforcement in composites because they have many benefits, such as high strength, durability, and resilience to different environmental variables. However, there are serious negative effects on the environment and human health associated with the manufacture and use of synthetic fibres. The creation of synthetic fibres, particularly those derived from raw materials derived from petroleum, has a significant environmental cost. Environmental pollution results from the widespread usage of synthetic fibres, which also presents disposal issues at the conclusion of the product lifecycle [3]. Glass fibre is one of the most popular synthetic fibres used in composite applications, particularly in the boat hull construction sector. Although fibreglass has good mechanical qualities, is waterproof, and requires little upkeep, its long-term environmental effects and disposal challenges have caused serious concerns. Fiberglass's toughness and endurance allow it to be used with a wide range of building materials, but at the end of its lifecycle, its properties make recycling and disposal more difficult, which causes waste management problems.

However, for thousands of years, people have used natural fibres made from plants, animals, and minerals for a variety of uses, from clothing to shelter. Because of their sustainability, biodegradability, and minimal environmental impact, these fibres are becoming more and more popular in composite materials [4]. Natural fibres are especially appealing for green engineering applications since they are environmentally beneficial and renewable, in contrast to synthetic fibres. Cultivating and using kenaf in industrial settings, including for automotive components, helps mitigate climate change by lowering the demand for wood and other non-sustainable resources, which further lowers CO_2 [5]. However, natural fibres have certain intrinsic disadvantages, such as lower processing temperatures, more moisture absorption, and poorer strength when compared to synthetic fibres [6]. Their usage in high-performance applications where synthetic fibres like glass or carbon fibre predominate has long been restricted by these problems.

One of the main reasons natural fibres haven't been able to completely replace synthetic fibres in structural composites is their low strength and mechanical qualities. Researchers have created hybrid composites, which blend the greatest qualities of synthetic and natural fibres, to get around these restrictions. These hybrid composites combine synthetic fibres like glass fibre with natural fibres like kenaf to provide a special blend of strength, weight reduction, and environmental advantages. With the fibreglass providing the high strength needed for demanding applications and the kenaf fibres offering sustainable reinforcement, the hybridization of these fibres produces a composite material with remarkable mechanical performance [7]. Hybrid composites have been suggested by researchers as a way to lessen the drawbacks of natural fibres while lowering dependency on artificial, non-sustainable materials [8].

It is essential to test these hybrid composites' mechanical qualities to make sure they can withstand the demanding requirements of real-world applications. One of the most significant mechanical tests is tensile testing, which offers vital information on properties including ductility, yield strength, and tensile strength. Engineers can determine the force needed to stretch a material and the amount of elongation it experiences before rupture by subjecting a specimen to uniaxial strain until it fails. These measurements are essential for figuring out how well the material performs under stress and making sure it can support the loads that are anticipated in practical applications. Additionally, in sectors like structural construction and maritime engineering, where materials must function dependably under both constant and changing stresses, tensile testing aids in forecasting how composite materials will behave [9].

Material optimisation can be significantly improved by integrating machine learning techniques, especially Artificial Neural Networks (ANNs), after experimental data has been gathered. Analysing complicated datasets is made possible by ANN algorithms, which are strong instruments that can reveal patterns, correlations, and anomalies that conventional analytical techniques could miss [10]. ANNs increase the predictive accuracy of material models and help researchers comprehend intricate interactions between factors. Based on a variety of input variables, including fibre loading, matrix type, and processing conditions, ANN models may forecast the mechanical properties of hybrid composites in the context of composite materials. Advanced training algorithms like Levenberg-Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG) are used in conjunction with ANN models to help researchers optimize their models and produce more accurate predictions about the behaviour of composite materials under various circumstances. During training, these methods modify the neural network's weights and biases to guarantee that the model can correctly forecast the strength, durability, and other mechanical properties of the composite. The efficiency and dependability of composite materials for industrial applications are improved by the use of ANNs in material science, which also speeds up the design and optimization process.

The creation of hybrid composites, which combine the advantages of natural and synthetic fibres, is a result of the rising need for high-performance composite materials in structural applications as well as environmental concerns about synthetic fibres [6, 8]. With the aid of cutting-edge computational methods like machine learning, testing and optimization of these composites have enormous potential to enhance the mechanical performance, sustainability, and affordability of composite materials utilized in sectors like civil infrastructure, aviation, and maritime. Without sacrificing structural integrity, natural fibres can be used into composite compositions to lessen environmental effects and encourage the use of eco-friendly products. Materials that can satisfy the exacting specifications of contemporary engineering applications will become more economical, efficient, and sustainable as a result of the ongoing development and use of these cutting-edge techniques.

2. METHODOLOGY

2.1 Materials

Polyester resin (Reversol P-9509) was used as the polymer matrix, while surface-treated kenaf fibres and chopped strand mat (CSM) 225 fibreglass were used as reinforcement materials to create the Kenaf/Fiberglass Polyester Reinforced Hybrid Composite materials. To get rid of impurities, lower the amount of lignin, and smooth up the surface, the natural kenaf fibres were chemically treated, usually with alkaline treatment (NaOH). The interfacial adhesion between the hydrophilic natural fibres and the hydrophobic polyester resin is greatly improved by this surface modification, which is essential for improving mechanical qualities and long-term stability. The natural kenaf fibre that used in the fabrication (Figure 1).

Figure 1. Kenaf fibre

Because of its uniform fibre orientation and simplicity of impregnation with the polyester resin, the fibreglass component CSM 225 (Figure 2) was chosen for reinforcing applications that demand durability and homogeneous stress distribution.

A balanced composite that combines the strength and water resistance of fibreglass with the affordability, renewable nature, and biodegradability of kenaf is made possible by the hybrid format of natural and synthetic fibres.

Figure 2. CSM 225 (Fibreglass)

The controlled hand lay-up method, a popular technology in composite fabrication that enables uniform resin application and exact fibre mat placement, was utilised to fabricate the composite [11]. In order to improve compaction, remove air gaps, and guarantee consistent fibre dispersion throughout the matrix, the laminates underwent compression moulding after the hand lay-up. In addition to strengthening the fiber-to-matrix link, this procedure lessens the possibility of internal flaws that could impair mechanical performance, like delamination or void formation.

The resulting hybrid composite is a promising candidate for lightweight, sustainable structural applications in a variety of industries because of its optimised internal structure and enhanced tensile, flexural, and impact strength properties, which are guaranteed by this meticulous fabrication process.

2.2 Fabrication process

Different weight ratios of fibreglass and kenaf reinforcements in relation to the polyester resin matrix were used to create the hybrid composite samples. This was done in order to evaluate the effects of varying fibre loading levels on the Kenaf/Fibreglass Reinforced Polyester Hybrid Composite's tensile strength. 15%, 45%, 60%, and 75% fiber-to-resin weight compositions were made for testing, and a control sample with 0% reinforcement (pure polyester resin) was also made. The quantity of reinforcing fibres in the composite is represented by these proportions, and it has a major impact on the material's resistance to tensile stresses.

The polyester resin (Reversol P-9509) was completely combined with a catalyst, usually methyl ethyl ketone peroxide (MEKP), to start the polymerisation and curing process and start the fabrication process. The MEKP was added at a concentration of 2% by weight of the resin to ensure proper curing based on industry standard practice. For all specimens to exhibit consistent mechanical behaviour and appropriate curing, uniform mixing was necessary.

To ensure a precise fit in the mould, the kenaf and CSM fibreglass layers were manufactured with conventional specifications of 230 mm for length, 160 mm for breadth, and 5 mm for thickness. Because of its ease of use and efficiency in producing laminate composites with regulated fibre distribution, the hand lay-up process was selected for the fabrication. To avoid sticking and make it easier to demould after curing, the mould surface was coated with wax and a release agent before the lay-up.

Layers of fibreglass and kenaf were alternately inserted into the mould during the fabrication process, according to the desired weight % for each sample. To guarantee complete impregnation and remove air pockets between layers, polyester resin was applied to each layer using a brush and roller. In order to improve resin-fibre interaction, reduce voids, and encourage consistent thickness across the laminate, a roller was employed to compress the material after each layer. The layering process is shown in Figure 3.

Figure 3. Hand lay-up process

The curing process was conducted at room temperature, approximately 28–32°C, under ambient humidity conditions typical of Malaysia's tropical climate (around 70–85% relative humidity), with an initial curing time of 24 hours followed by an additional 48 hours of post-curing at the same temperature to ensure complete cross-linking of the polymer matrix.

The panels were demolded and cut to size after curing, resulting in specimens that met tensile testing requirements. Later, tensile tests were performed on these specimens to assess how well they performed mechanically under uniaxial tension.

Each sample's designation is shown in Table 1 according to the weight proportion of fibreglass and kenaf. Tensile test findings precisely represent the impact of fibre composition on the hybrid composite's mechanical strength, thanks to the methodical and consistent fabrication process.

Table 1. Designation of each weight percentage materials

Percentage of Materials (%)	0% (Control Sample)	15%	45%	60%	75%
Polyester + Catalyst	90	75	45	30	15
Natural Fibres (kenaf)	0	15	45	60	75
Fibreglass	10	10	10	10	10

2.3 Tensile testing

The American Society for Testing and Materials (ASTM) D3039 standard was followed in evaluating the manufactured kenaf/fibreglass reinforced polyester hybrid composites' tensile strength. The process for figuring out the tensile properties of polymer matrix composite materials reinforced with high-modulus fibres is described in this standard approach. An Instron Universal Testing Machine, which has sophisticated load cell and data collecting technologies to guarantee excellent precision and reproducibility in mechanical testing, was used to perform the tests.

To prevent adding edge flaws that would affect the results, each composite panel was meticulously sliced into tensile test specimens, or "coupons," using a precision cutting tool. As advised by ASTM D3039 rules, the specimens were constructed in the shape of a rectangular ruler, measuring 250 mm in length and 20 mm in width. Although it was kept within reasonable bounds for a precise comparison, the coupons' thickness varied somewhat based on the fibre content.

Five test coupons were made for each of the fibre loading parameters: 0% (control), 15%, 45%, 60%, and 75%. This made it possible to evaluate tensile strength with statistical reliability. Before testing, every coupon was examined visually for flaws that could affect the structural integrity or cause variations in the test findings, such as surface voids or delamination.

The testing equipment was adjusted to a constant crosshead speed of 2 mm/min to apply a consistent rate of load throughout elongation, and the tensile test was conducted at room temperature. In order to reduce environmental variability, tensile tests were conducted under ambient lab conditions (25 ± 2℃, 60 ± 5% RH) to minimize environmental variability. To avoid slippage or uneven loading, the specimens' ends were firmly fastened in the machine grips. The machine recorded each sample's stress-strain response as the load was applied until it failed.

Calculating the highest stress the composite could sustain before breaking allowed for the determination of the Ultimate Tensile Strength (UTS). The following formula was used to calculate it:

$$\text{UTS, } \sigma_{\max} = \frac{P_{max}}{A_0}$$

where, P_{max} is the maximum load applied (N) to the composite and A_0 is the area of the cross-section (mm^2).

In order to minimise any irregularities or inconsistencies, five samples per configuration were tested, following ASTM D3039. This number is suggested for classical methodology as in laboratory experiment to obtain the average performance of the sample [12]. Each tensile test was repeated five times per group, and the results are presented as mean ± standard deviation to ensure reproducibility and statistical validity as per ASTM D3039. Clear insights into how varying fibre content levels affect the hybrid composites' mechanical behaviour under tensile stress were revealed by the resulting data. In order to spot patterns and determine the ideal composition that produces the best tensile performance, these data were subsequently compared.

2.4 ANN optimization

The complex, nonlinear relationship between fibre weight percentage (%), composite thickness (mm), defect levels, and the tensile strength of hybrid polymer composites reinforced with kenaf and fibreglass was modelled in this study using a Multi-Layer Perceptron (MLP) neural network. Predicting the composites' tensile behaviour using quantifiable input factors and evaluating the impact of each variable on mechanical performance were the goals. The Neural Network Fitting Tool in MATLAB®, a powerful platform frequently used in engineering applications for machine learning and data-driven modelling, was employed to carry out the modelling procedure.

Scanning Electron Microscopy (SEM) analysis and visual inspection were used to assess the composite samples' defect levels. A qualitative rating system from Level 1 to Level 5 was used in the assessment; Level 1 denotes outstanding quality with few noticeable flaws, while Level 5 denotes very low quality with many flaws. More serious flaws include fibre pull-out, matrix cracking, delamination, and poor fiber–matrix adhesion is correlated with higher defect levels. This qualitative classification has inherent limits in terms of objectivity and precision, even if it offered helpful initial insights into the structural integrity and failure processes of the composites. Future studies will therefore use quantitative methods, such as image-based analysis, to quantify variables including crack density, fibre orientation, and void. Using advanced image processing technologies, these metrics will be retrieved from high-resolution SEM pictures, providing a more reliable and repeatable way to assess the severity of defects.

Initially, the min-max normalization technique was used to pre-process the experimental dataset, which was gathered from physical tensile tests. Min-Max normalisation was applied to scale all variables within the range of 0 to 1 using the following equation:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

By ensuring that every input contributes equally during the training process, this normalisation strategy helps to prevent bias towards variables with wider ranges of numbers. Defect level (1–5), composite thickness (5.0–6.0 mm), and fibre weight percentage (15–75%) were the minimum and maximum parameters utilised for normalisation.

In order to ensure that every feature contributes proportionately to the model training process and to prevent bias caused by different units or magnitudes, this normalisation method was chosen to scale all input parameters into a consistent range, usually between 0 and 1 [13]. During training, this pre-processing phase improves the neural network's accuracy and pace of convergence. To guarantee a fair assessment of the model's accuracy and generalization potential, 70% of the data was used to train the model, 15% was put aside for validation to improve the model and avoid overfitting, and the remaining 15% was used for performance assessment and final testing [14].

The neural network was subjected to three distinct training procedures to evaluate how well each one optimised the model's functionality. These consist of the SCG, LM, and BR methods, each chosen for its distinct advantages in managing nonlinear regression issues. In small-to-medium-sized datasets, LM is renowned for its quick convergence and high accuracy [15], but BR effectively reduces overfitting by adding a regularisation term [16]. SCG provides dependable performance and is frequently chosen for large datasets despite being computationally lighter [17]. The study sought to ascertain which training strategy would produce the most reliable and accurate model for forecasting the composites' tensile strength by utilising all three algorithms.

Iterative trial-and-error optimisation was used to further optimise the neural network design, which started with a default configuration of 3:6:2 as is Figure 4 (input layer: hidden layer: output layer). To determine the optimal arrangement, this procedure entailed altering the number of hidden layers from one to six and modifying the number of neurones within each layer. A widely recognised heuristic was used to direct this optimisation, which states that in order to avoid model overfitting and guarantee generalisation ability, the hidden layer's neurone count should typically be less than twice that of the input neurones [18]. In order to minimise error and maximise the model's predictive power, the final design was chosen based on the model's performance measures, such as the Mean Squared Error (MSE) and correlation coefficient (R-values).

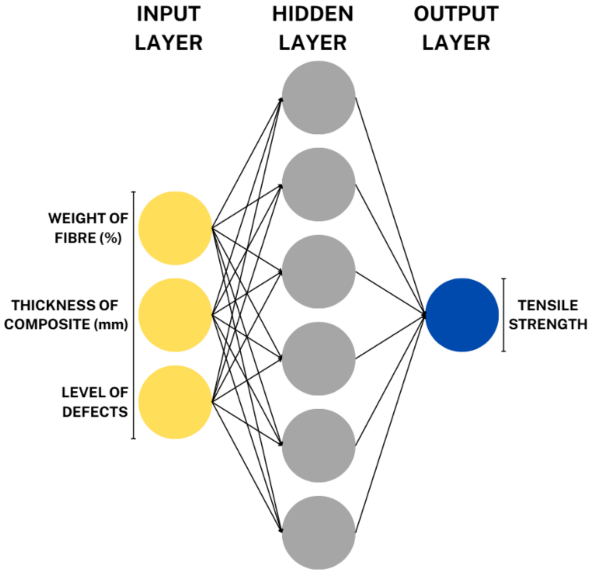

Figure 4. Neural network architecture

The final ANN model fitted the regression-based prediction by using a linear activation function in the output layer and a Rectified Linear Unit (ReLU) activation function in the hidden layer. Full-batch learning using the Adaptive Moment Estimation (Adam) optimiser, 1000 epochs, and a fixed learning rate of 0.01 were used for training. 70% of the dataset was used for training, 15% for testing, and 15% for validation. This division was made at random. To perform a generalisation test and confirm the model's prediction power, an additional 70% random subset of the data was taken out. To ensure the correctness and robustness of the trained model, the model's performance was assessed using common regression metrics, such as Mean Squared Error (MSE) and the R-squared (R^2) value.

Three different parameters as shown in Table 2, made up the network's input layer: the weight percentage of fibre, the thickness of the composite, and the degree of defect. These parameters were chosen because they were found to have a significant impact on the material's tensile performance in testing results. The model's comprehension of how each component influences the composite's mechanical reaction is based on these parameters. Six neurones made up the hidden layer at first, however throughout optimisation, this number was changed as necessary. Based on the given input parameters, the output layer was intended to generate a single value that represented the composite's anticipated UTS.

Table 2. Processing parameters for tensile strength

Weight of Fibre (%)	Thickness of Composite (mm)	Level of Defects
15 45 60 75	5.00 5.50 6.00	1 (Excellent) 2 (Fair) 3 (Moderate) 4 (Poor) 5 (Very poor)

Due to experimental limitations, the current model focused on three primary inputs due to their strong experimental relevance. Future studies will include additional parameters such as fibre orientation and curing time to enhance model generalizability.

3. RESULT AND DISCUSSION

3.1 Ultimate tensile strength

A thorough examination of tensile strength was carried out across a variety of fibre weight percentages in order to assess the effect of natural fibre loading on the mechanical performance of the Kenaf/Fiberglass Reinforced Polyester Hybrid Composite. Tensile strength and fibre content were found to be strongly correlated as in Figure 5, and the addition of kenaf fibres considerably enhanced mechanical performance, although to a limited scale.

The composite showed a steady increase in tensile strength up to a weight percentage of 45% kenaf fibre. This finding implies that with this fibre loading, the natural kenaf fibres and the synthetic fibreglass reinforcement were in the best possible proportion. The ability to transfer tensile loads was improved by the kenaf fibres' efficient reinforcement in the composite matrix. The fibres' and the polyester matrix's well-balanced interfacial interaction, which promotes effective stress transmission and improved load distribution throughout the material, is responsible for this synergistic impact. As a synthetic fibre, the fibreglass reinforcement provided exceptional strength and durability, complementing the natural fibres and adding to the hybrid composite's overall enhanced mechanical qualities.

At 45% of kenaf fibre content, the highest tensile strength was recorded, indicating that this particular composition is the ideal matrix-fiber interaction point. Superior interfacial adhesion, fibre dispersion, and uniform stress distribution were the results of optimal matrix-fiber bonding, as demonstrated by the composite's performance at this fibre concentration. These elements helped the material achieve its ideal tensile strength and overall mechanical integrity. Conversely, as anticipated, the control sample, which was made entirely of the polyester matrix with no reinforcement, showed the lowest tensile strength. This outcome demonstrated how crucial fibre reinforcing is to improving the mechanical qualities of composite materials.

However, a discernible decrease in tensile strength was noted as the kenaf fibre content rose above the 45% threshold, especially at 60% and 75%. This decrease is mostly due to the higher concentration of natural fibres in the matrix, which caused the fibres to aggregate, disperse poorly, and form weak interfacial bonds with the matrix. Natural fibres have a tendency to group together at greater fibre loadings, which can cause irregular fibre distribution and make it more difficult for stress to be transferred from the matrix to the fibres. Furthermore, microstructural flaws including void formation, fibre pull-outs, and irregular fibre orientation are made worse by excessive fibre loading, all of which lower the structural integrity of the composite. Defect analysis corroborated these findings, showing that composites with increased fibre content exhibited more voids and uneven fibre distribution, which further weakened the mechanical capabilities of the material.

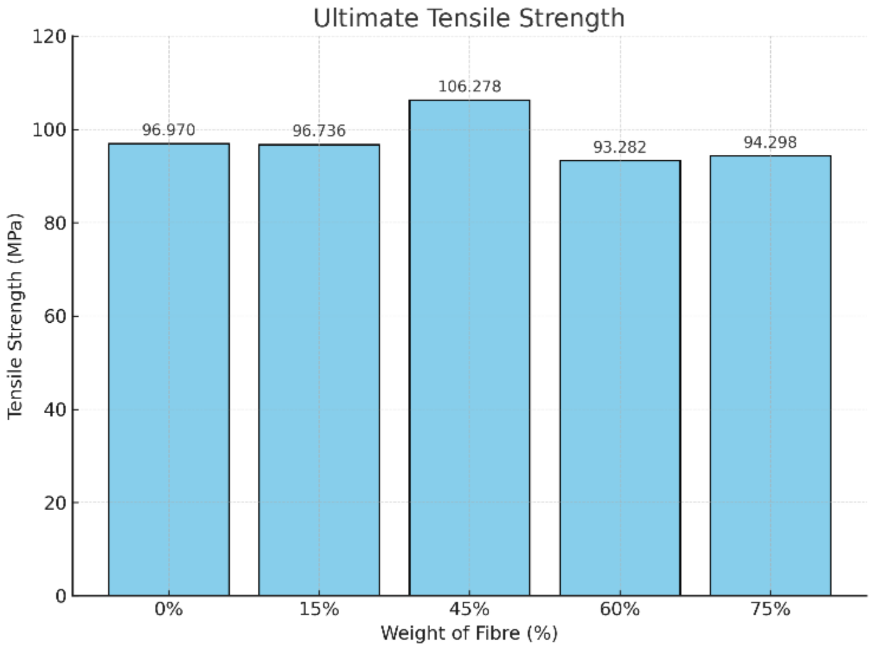

Figure 5. Ultimate tensile strength

The hydrophilic properties of natural fibres, such as kenaf, are important factors in this deterioration at larger fibre loadings, according to the defect analysis. Because of their propensity to absorb moisture, natural fibres may have trouble connecting with the hydrophobic polymer matrix. Poor fiber-matrix adhesion results from a weakening of the link between the kenaf fibres and the polyester matrix as the moisture content rises. The overall strength of the composite is further compromised by the excessive presence of natural fibres, which breaks the continuity of the polymer matrix. These results are in line with earlier studies that show that excessive loading of natural fibres tends to reduce composite strength even if they can greatly improve mechanical qualities when utilized in the right amounts. Thus, maintaining a balance between the reinforcement's contribution and the composite's structural integrity requires optimizing the fibre loading.

The study's findings highlight how crucial it is to carefully choose and maximize the fibre content in hybrid composites, especially when trying to achieve a balanced blend of synthetic and natural fibres. It has been demonstrated that combining kenaf and fibreglass greatly improves the composite material's mechanical qualities, providing a more environmentally friendly substitute for conventional composite materials without sacrificing structural integrity. But this study also highlights how important fibre loading is to getting the greatest mechanical qualities. The benefits of natural fibre reinforcement and the drawbacks of an excessive fibre content are perfectly balanced by the 45% kenaf fibre loading.

To sum up, this study's results emphasize how crucial it is to combine natural and synthetic fibres to create high-performance composite materials. The mechanical strength of these materials may be increased by carefully regulating the fibre quantity and guaranteeing ideal dispersion and fiber-matrix adhesion. This makes them appropriate for a variety of structural applications, including those in the automotive and maritime sectors. The study also emphasizes how important it is to optimize material compositions in order to satisfy performance criteria and environmental sustainability goals. Future studies could look into ways to improve fibre dispersion at higher fibre loadings, possibly by adding more surface treatments to promote fiber-matrix compatibility or by using sophisticated processing techniques. Furthermore, more research on these hybrid composites' long-term resilience to several environmental factors, like moisture exposure or thermal cycling, will be helpful in improving the materials' performance forecasts.

3.2 ANN analysis

Three crucial parameters, fiber weight percentage, composite thickness, and defect levels, were used to forecast the tensile strength of Kenaf/CSM fibreglass reinforced polyester hybrid composites using ANN modelling. These input factors were selected due to their known influence on the mechanical performance of fiber reinforced composites. The predictive strength of the ANN technique lies in its ability to simulate complex and nonlinear relationships between input data and output responses, which are often difficult to capture using traditional statistical or analytical models. Table 3 presents the compiled results for each training algorithm.

Among the three training methods used in the ANN modelling of tensile strength for kenaf/CSM fibreglass reinforced polyester hybrid composites, the LM approach demonstrated the best performance. This was evident from its superior statistical indicators, including the highest R values and the lowest MSE across all phases of model evaluation: training, validation, testing, and overall analysis. The R values achieved by the LM algorithm were 0.9686 for overall, 0.9846 for testing, 0.9999 for validation, and 0.9686 for training. These results indicate excellent model performance and a very strong linear relationship between the predicted and actual experimental outcomes.

Table 3. Performance indicator of the training algorithm

Training Algorithm	PI	Training	Validation	Testing
LM	MSE	0.0063	0.0075	0.0053
	R	0.9686	0.9846	0.9999
BR	MSE	0.0053	-	0.0158
	R	0.9653	-	0.9911
SCG	MSE	0.009	0.009	0.011
	R	0.9351	0.9808	0.9647

Figure 6 shows the regression plot of tensile strength for LM training algorithm. This finding is further supported by the regression graphs produced for the LM model. There seemed to be little difference between the observed and anticipated values, as the forecasted data points nearly matched the optimum fit line (Y = T). This level of precision demonstrates how well the LM algorithm handles the intricate and nonlinear relationships between the three main input parameters that affect the hybrid composite's tensile strength: fibre weight percentage, composite thickness, and defect levels. The superiority of LM can be ascribed to its distinct optimisation strategy, which blends the Gauss-Newton algorithm with the gradient descent method [19]. Even with noisy or nonlinear data, the algorithm can converge quickly because of this hybrid approach, which makes it possible to minimize the error function more effectively. Because of its resilience, LM is particularly well-suited for materials science applications where input-output interactions frequently involve numerous sources of uncertainty and are rarely linear.

On the other hand, although it performed marginally worse overall than LM, the BR algorithm likewise yielded very good predictions. The resultant R values, which were 0.9653 for training, 0.9911 for testing, and 0.9514 for overall, continue to show a high degree of agreement between the experimental and predicted values of tensile strength. Even though BR's MSE was slightly higher than LM's, the model demonstrated exceptional stability and resistance to overfitting, which is a big plus when working with sparse datasets or ambiguous measurement conditions. This is mostly because the BR algorithm's built-in regularization technique introduces a penalty term into the performance function. This feature guarantees that the ANN retains its generalizability when exposed to unknown input and helps keep the model from growing unduly complex.

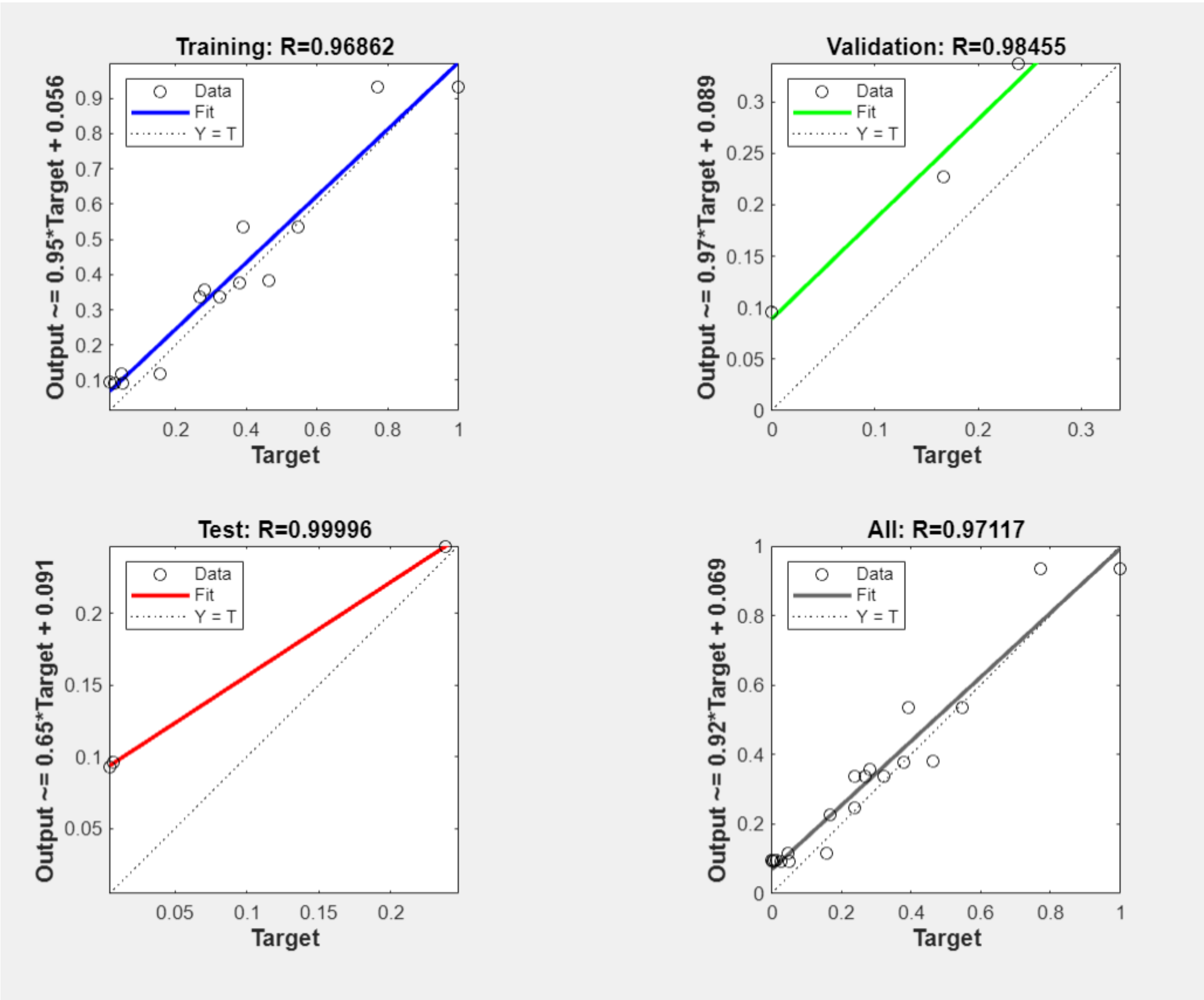

Figure 6. Correlation for actual and predicted tensile strength for Levenberg-Marquardt (LM)

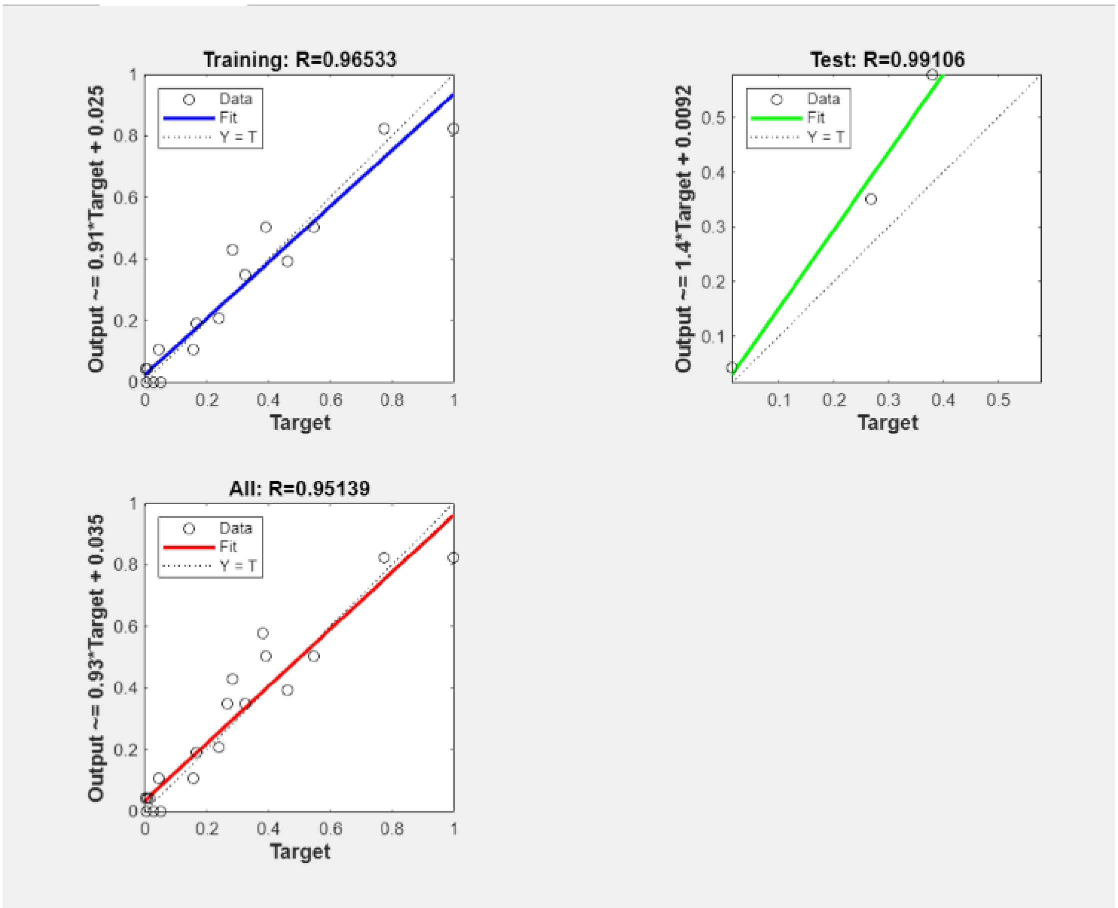

Figure 7. Correlation for actual and predicted tensile strength for Bayesian Regularization (BR)

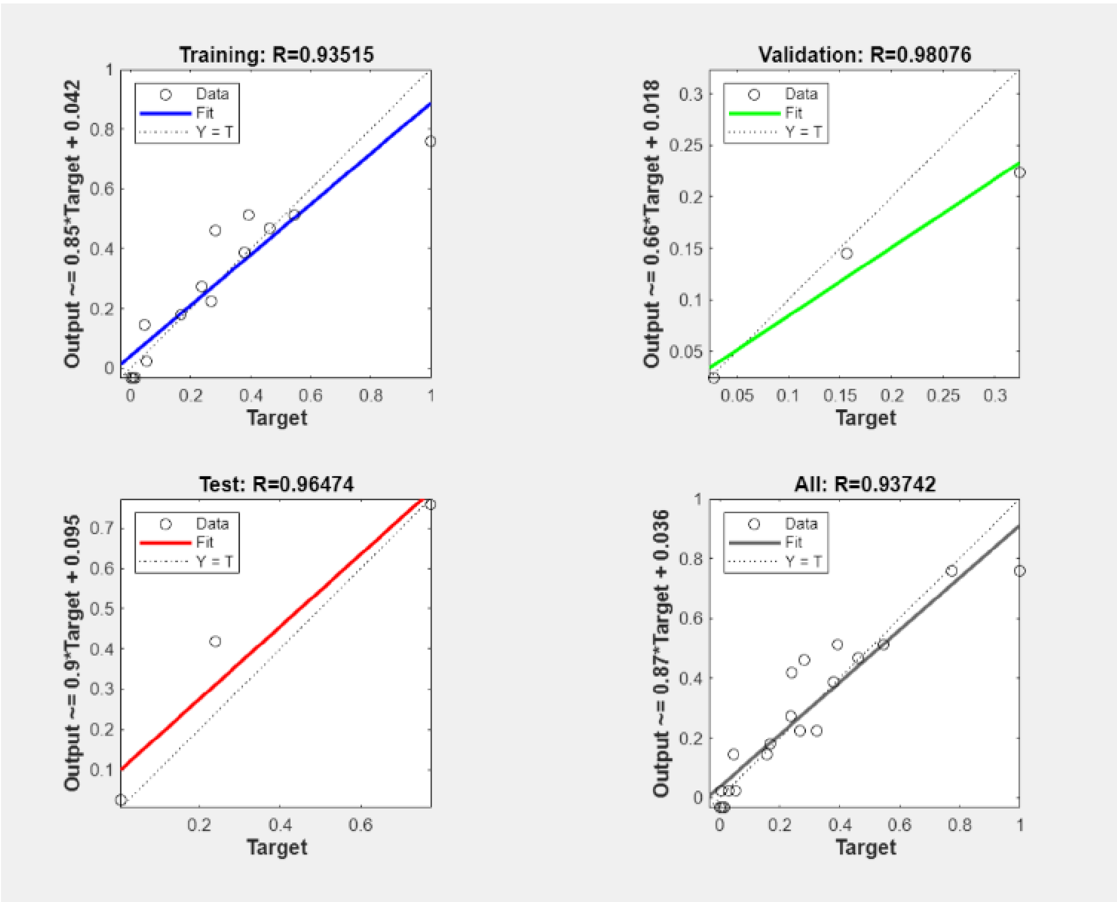

Figure 8. Correlation for actual and predicted tensile strength for Scaled Conjugate Gradient (SCG)

Figure 7 shows the regression plot of tensile strength for BR training algorithm. With just slight departures from the optimum fit line, the regression plots for the BR model similarly showed a strong agreement between the expected and actual values. This implies that BR can accurately model the intricate linkages seen in the composite system. Even though BR's prediction accuracy was slightly lower than LM's, it is still a very dependable approach, particularly in situations where robustness and avoiding overfitting are more important than exact prediction accuracy.

The SCG, the third algorithm under evaluation, performed the least well out of the three, although it still produced results that were passably good. The SCG model's recorded R-values were 0.9374 (overall), 0.9808 (validation), and 0.9352 (training). These numbers show a reasonable degree of connection between the expected tensile strength and the actual experimental values, albeit being lower than those obtained by LM and BR. A greater degree of forecast variability was indicated by the SCG regression plots, which showed a wider distribution of data points around the optimal fit line. This implies that, in comparison to LM and BR, the SCG model struggled more to generalize the intricate nonlinear interactions and had somewhat lower consistency.

The simplified optimization procedure of the SCG algorithm, as in Figure 8, which sacrifices computational efficiency for predictive capacity, may be the cause of its comparatively poorer performance. SCG is based on a conjugate gradient approach, which might not be as effective at adjusting to the complexities of highly nonlinear material behaviour as LM and BR, which use adaptive error minimization and regularization techniques [20]. For larger datasets or real-time applications with constrained processing resources, its reduced memory requirements and quicker computation times nevertheless make it a desirable option.

Overall, the complex, nonlinear relationships between the fibre content, composite thickness, defect levels, and their combined effect on tensile strength were effectively captured by the ANN model used in this investigation [21]. This was particularly clear from the LM algorithm's performance, which yielded incredibly high R-values and a low MSE, indicating a robust and reliable predicting ability. These findings support the usefulness of ANN-based modelling in materials engineering and offer a potent substitute for time-consuming, resource-intensive, and experimentally limited traditional empirical techniques.

Furthermore, the results of this modelling experiment highlight ANN's potential as a tool for hybrid composite design optimization. ANN speeds up formulation cycles, improves resource efficiency, and enhances decision-making throughout the development phase by eliminating the need for extensive trial-and-error testing. While reducing material waste and development expenses, it enables researchers and engineers to find the best combinations of fibre reinforcement, matrix composition, and structural properties that satisfy certain mechanical performance requirements.

In the future, there will be many chances to improve and expand the use of the ANN framework created in this work. To anticipate composite behaviour under real-world conditions, the current model can be expanded to include environmental and service condition factors, such as exposure to freshwater or saltwater, temperature cycling, UV radiation, or long-term ageing effects [22]. By adding more varied information and broadening the network architecture, it is also possible to mimic attributes like fatigue performance, flexural strength, and impact resistance.

In the end, incorporating machine learning technologies such as ANN into advanced composites' design, analysis, and lifecycle prediction provides a method to create material systems that are more intelligent and sustainable [23]. It backs the larger trend towards green engineering, in which high-performance materials are created with consideration for resource efficiency and environmental impact. As demonstrated in this work, the knowledge gathered from ANN modelling not only speeds up the creation of environmentally friendly hybrid composites but also fosters innovation in the materials field by facilitating better-informed, data-driven engineering methods.

4. CONCLUSION

By employing hand lay-up procedures and ANN modelling to examine and optimise the tensile properties of Kenaf/CSM fibreglass reinforced polyester hybrid composites, this study effectively achieved its goal. Due to the best fibre dispersion and robust interfacial interaction between the fibres and matrix, the composite with a 45% weight percent kenaf content had the maximum tensile strength, measuring 50.47 MPa. With an R value of 0.9686 and a MSE of 0.0063, the ANN model, which was trained using fibre weight percentage, composite thickness, and defect level as input parameters, showed excellent predictive accuracy using the LM technique. These results demonstrate how well experimental testing and ANN modelling work together to minimise trial-and-error in composite design and enhance material performance. The optimized composition (45% kenaf) is being considered for marine applications, with prototype testing planned in collaboration with industry. It is recommended that future research evaluate the composites' resilience to environmental factors like moisture and heat exposure, investigate improved fibre treatments and cutting-edge fabrication techniques like vacuum infusion, and extend the ANN model to forecast more mechanical attributes like flexural strength, impact resistance, and fatigue life for broader structural applications. Although the ANN model showed good predicted accuracy for the current investigation, it has not yet been evaluated to see if it can be applied to different fibre kinds and matrix systems. Future studies should examine the model's scalability to industrial-scale production and a broader range of material systems, as it is currently restricted to lab-scale composite samples.

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