



PREDICTING BENDING STRENGTH OF PHILIPPINE BAMBOO SPECIES USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT: Bamboo has gained attention as a sustainable structural material because of its advantageous strength-to-weight ratio and rapid renewability. However, the variation in its mechanical properties across species and geometric characteristics presents challenges for reliable structural design, while multispecies data-driven prediction of bamboo bending strength remains limited. This study reported standardized bending test data and developed an artificial neural network (ANN) model using pooled experimental data from five bamboo species. Four-point bending tests were conducted on four species following ISO 22157, while data for one additional species was obtained from a previously published study. The pooled dataset comprised 313 specimens. Mean bending strengths ranged from 64 to 84 MPa, with coefficients of variation of 20-26%, demonstrating material variability. The ANN used outer diameter, wall thickness, moisture content, density, thickness-to-diameter ratio, and the density-thickness product as predictors. The optimized model achieved a test R^2 of 0.89, RMSE of 6.76 MPa and MAPE of 3.08%. Repeated validation across multiple random seeds produced a mean test R^2 of 0.807 ± 0.094 , providing an additional assessment of predictive performance across alternative data partitions. Permutation feature importance indicated that the trained ANN relied most strongly on wall thickness. The resulting framework may support preliminary bending-strength estimation within the geometric and physical domain represented by the pooled dataset.

Keywords: Bamboo, Bending strength, Artificial Neural Network, Mechanical Properties

1. INTRODUCTION

Bamboo has emerged as a promising renewable construction material due to its high strength-to-weight ratio, rapid growth rate, and wide availability in tropical regions [1-3]. Growing interest in sustainable construction has encouraged its use in structural applications, including engineered bamboo products and composite structural systems [4,5]. In these applications, bamboo members may be subjected to flexural actions making bending strength an important property for beams, purlins, and truss members.

Approximately 62 species have been identified in the Philippines, however standardized mechanical data remain limited [6]. Previous research has established selected parameters of Philippine grown *Dendrocalamus asper*, but locally available information remains concentrated on a limited number of species and mechanical properties [7]. This lack of data restricts material grading, structural assessment, and development of design values. ISO 22157 specifies procedures for determining physical and mechanical properties of bamboo, whereas ISO

22156 provides structural design provision and ISO 12122-1 outlines procedures for deriving characteristic values [8-10]. Despite the availability of standardized procedures, comprehensive mechanical testing requires substantial specimen preparation, labor, time, and equipment. The natural variability of bamboo further necessitates sufficiently large samples to obtain representative mechanical properties [11-14]. Applying the provisions to numerous species with potential to structural application is therefore challenging.

Previous studies have established that bamboo mechanical properties are influenced by culm geometry, density, and moisture content [15]. Outer diameter and wall thickness describe culm dimensions, while density and moisture content represent material condition. Pooling observations from multiple species may therefore allow shared relationships between these measurable parameters and bending strength to be investigated across a broader material domain.

Artificial neural networks (ANNs) are computational models capable of learning complex nonlinear relationships between input variables and

target responses [16]. In materials and structural engineering, ANN models have been applied to predict the flexural strength of cement-based composites, hardened properties of geopolymer concrete, bond strength of corroded reinforcement, compressive strength of foam concrete, direct tensile strength of bamboo-fiber-reinforced concrete, and 28-day compressive strength of concrete under job-site conditions [17-22]. These applications demonstrate the potential of ANNs to approximate mechanical responses governed by interacting material, physical, and geometric parameters. This capability is particularly relevant to bamboo because its bending strength is jointly influenced by culm geometry, density, and moisture condition.

More recently, data-driven approaches have been applied to bamboo and other sustainable materials. Yang et al. used an optimized backpropagation neural network to predict the flexural properties of flattened bamboo slices, while Makhatha et al. compared ANN and response surface methodology for predicting the mechanical strength of chemically modified bamboo fibers [23, 24]. Rehman et al. applied ANN to predict the mechanical and fracture responses of eco-friendly engineered composites [25]. Furthermore, Muhammad et al. evaluated synthetic-data-generation methods for ANN-based bamboo-property prediction [26]. However, these studies primarily concerned processed bamboo components, isolated bamboo fibers, engineered composites, or data-augmentation techniques rather than the direct prediction of bending strength from standardized full-culm tests involving multiple Philippine bamboo species. Consequently, pooled multispecies ANN modeling of the bending strength of Philippine bamboo culms remains insufficiently investigated.

The present study reports standardized four-point bending test data for four Philippine bamboo species and develops a pooled multispecies ANN model for predicting bending strength. The newly generated experimental data were combined with compatible published data for one additional species, producing 313 observations. Outer diameter (OD), wall thickness (T), moisture content (MC), density (D), derived variables T/OD and $D \times T$ were used as model inputs. The model was developed and optimized, evaluated through independent testing and repeated validation, and compared with multiple linear regression as a baseline. Correlation and permutation feature importance analyses were also performed to examine the contributions of the input parameters. The proposed framework is intended for preliminary bending-strength estimation within

the material domain represented by the available dataset and may provide a basis for future extension to other Philippine bamboo species following independent validation.

2. RESEARCH SIGNIFICANCE

The significance of this research contributes to several United Nations Sustainable Development Goals (SDGs). It advances SDG (Sustainable Cities and Communities) by promoting bamboo as a renewable structural material and developing tools for its wider use in construction. It contributes to SDG 12 (Responsible Consumption and Production) by enabling efficient preliminary material screening and more targeted destructive testing. The data-driven prediction of bamboo mechanical properties supports SDG 9 (Industry, Innovation and Infrastructure) through an innovative method for estimating structural performance. Finally, it aligns with SDG 13 (Climate Action) by encouraging resource-efficient and lower-carbon building practices.

3. MATERIALS AND METHODS

3.1 Data Collection

3.1.1 Material Preparation

This research experimentally investigated four Philippine bamboo species: *Bambusa merrilliana*, *Bambusa vulgaris*, *Dendrocalamus asper*, and *Guadua angustifolia*. The harvested bamboo poles ranged from 3 to 6 m in length were conditioned and treated with a permethrin solution before testing. The experimental dataset included 28 *Bambusa merrilliana*, 56 *Bambusa vulgaris*, 57 *Dendrocalamus asper*, and 21 *Guadua angustifolia* specimens. Previously published four-point bending data for *Bambusa blumeana* reported by Cacanando et al. [12] were incorporated into the pooled dataset. Although these observations were obtained from a separate publication, the specimens were tested in the same laboratory using the same four-point bending procedure prescribed in ISO 22157:2019, comparable specimen preparation and conditioning procedures, the same testing configuration, and consistent bending strength calculations as those applied to the other four species. The published dataset contributed 151 *Bambusa blumeana* observations, resulting in a pooled dataset of 313 observations from five Philippine bamboo species.

The datasets were therefore considered methodologically compatible for pooled ANN development. Nevertheless, possible differences associated with harvesting period, specimen age,

growing conditions, and other uncontrolled material factors may remain and are acknowledged as limitations of the integrated dataset.

3.1.2 Testing Procedure

The bending strength of the four experimentally investigated species was determined using the four-point bending test specified in ISO 22157:2019 [8]. Each full-culm specimen was simply supported and subjected to two symmetrically positioned loading points, as shown in Fig 1. Loading was continued until failure, and the maximum applied load was recorded. The bending strength, f_m , was calculated from the maximum load and measured specimen geometry following the procedure prescribed in the same standard.

Species-level characteristic bending strengths were estimated using the statistical procedure described in ISO 12122-1:2014 [10]. Because *Bambusa merilliana* and *Guadua angustifolia* were represented by 28 and 21 specimens, respectively, their estimated characteristic values are presented for preliminary comparison only. Additional standardized testing is required before these estimates can be adopted for formal material grading or structural design.



Fig. 1. Four-point bending test set up

3.2 Data Preprocessing

The pooled dataset contained geometric, physical, and mechanical parameters. The directly measured predictors were outer diameter (OD), wall thickness (T), moisture content (MC), and density (D). Density was adjusted to a reference moisture content of 12% using $D_{12} = D_{test} (112 / (100 + MC))$, where D_{test} is the density measured at the moisture condition during testing. The target variable was bending strength, f_m .

Two derived predictors were included to

represent relevant geometric proportions and material-geometry interactions. The thickness-to-diameter, T/OD, describes wall thickness relative to culm size, while the density-thickness product combines the adjusted density and wall thickness. Thus, the six ANN inputs were OD, T, MC, D, T/OD, and D×T.

Correlations were expected among the measured and derived variables because T/OD and D×T were calculated from primary predictors. These variables were retained because they provide physically meaningful descriptions of culm geometry and combined material-geometry characteristics. Their interrelationships and model-dependent contributions were subsequently examined using Pearson correlation analysis and permutation feature importance.

The bending strength was transformed using the natural logarithm to reduce skewness, stabilize the variance of the target distribution, and improve numerical stability during ANN training. After prediction, the model outputs were transformed back to their original units and all reported performance metrics were calculated in MPa. Bootstrap resampling was applied to expand the modeling dataset to 1200 samples through random sampling with replacement from the available observations [27]. The procedure increased the number of instances presented during ANN training while retaining the empirical characteristics of the original dataset. Because bootstrap samples are repetitions of existing observations rather than new experimental specimens, the procedure does not increase the amount of independent experimental information. Accordingly, the model results were interpreted within the material domain represented by the original pooled dataset.

All input variables and the transformed target were normalized to the range [-1,1] using min-max normalization. Normalization was applied to place variables with different units and numerical ranges on a comparable scale, thereby improving numerical stability and model convergence. Predicted target values were subsequently reverse-transformed and expressed as bending strength in MPa for evaluation and interpretation.

3.3 Model Development

An Artificial Neural Network (ANN) was developed to predict bamboo strength from six geometric and physical predictors. This input was chosen to identify relationship between measurable material properties and bending strength within the pooled multispecies dataset. The adopted network was a feedforward multilayer perceptron consisting

of an input layer, one or more hidden layers, and a single output layer representing the log-transformed bending strength. Species identity was not included as an input because the model was intended to predict bending strength using readily measurable geometric and physical properties within the pooled multispecies dataset. Figure 2 presents the general ANN architecture.

Eight candidate architectures containing one to four hidden layers and 10-30 neurons per layer were evaluated through a grid-search procedure. A hyperbolic tangent sigmoid function (tansig) was used in the hidden layers, while a linear activation function was applied in the output layer. Three MATLAB training algorithms were assessed for each candidate architecture: Levenberg-Marquardt (trainlm), scaled conjugate gradient (trainscg), and Bayesian regularization (trainbr). The optimal combination of network architecture and training algorithm was selected based on the lowest validation root mean square error (RMSE), calculated after transforming the predicted values back to the original MPa scale.

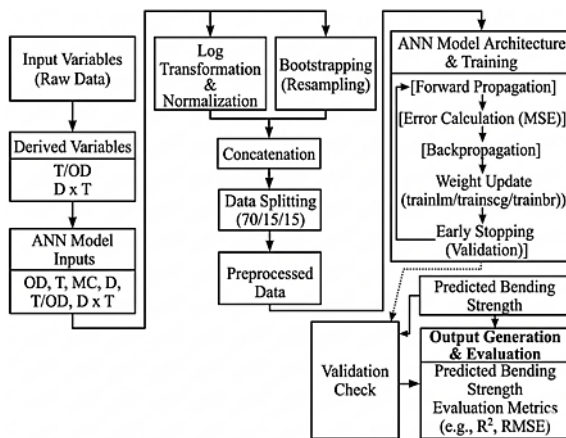


Fig. 2 Architecture of the feedforward multilayer perceptron used to predict strength

3.4 Training of the ANN Model

The preprocessed dataset was randomly divided into training, validation, and testing subsets using a 70:15:15 ratio. The training subset was used to estimate the network weights and biases, while the validation subset was used to monitor model performance and select the optimal network configuration. The testing subset was reserved for evaluating the predictive performance of the selected model.

During training, the input variables were propagated through the network to generate predictions of the log-transformed bending strength.

The difference between the predicted and target values was quantified using mean squared error (MSE), which served as the training loss function. The network weights and biases were iteratively updated according to the selected training algorithm.

Training was conducted for a maximum of 1000 epochs. For the selected Levenberg-Marquardt model, early stopping was applied when the validation performance failed to improve for 20 consecutive iterations. This criterion was used to limit overfitting while retaining the network parameters corresponding to the minimum validation error.

3.5 ANN Model Evaluation

The predictive performance of the ANN model was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). All metrics were calculated after the predicted log-transformed outputs were converted back to bending strength in MPa. The R^2 value describes the proportion of variation in the observed bending strength explained by the model, while RMSE and MAE quantify prediction error in MPa. MAPE expresses the average absolute prediction error relative to the observed value.

Model performance was reported separately for the training, validation, and testing subsets. The testing subset metrics were used as the primary indicators of predictive performance, while differences among the three subsets were examined to assess possible overfitting. For repeated validation R^2 and RMSE were summarized using their means and standard deviations to quantify model sensitivity to alternative data partitions and network initializations.

A multiple linear regression (MLR) model using the same six predictors was also developed as a conventional empirical baseline. Its testing performance was compared with that of the ANN using the same evaluation measures to assess whether the nonlinear ANN provided additional predictive value for the pooled multispecies dataset.

3.6 Model Testing and Assessment

3.6.1 Testing-Subset Evaluation

The optimized ANN model was evaluated using the testing subset generated during data partitioning, which represented 15% of the modeling dataset. This subset was excluded from network training and architecture selection and was used to assess the predictive performance of the selected model. The trained ANN generated predictions of log-

transformed bending strength, which were converted back to MPa and compared with the corresponding experimental values. Predictive performance was quantified using the statistical metrics described in Section 3.5. Regression and residual plots were also generated to examine the agreement between predicted and experimental bending strengths and identify patterns in the prediction errors.

3.6.2 Repeated Validation

Repeated holdout validation was performed using three random seeds to evaluate the sensitivity of model performance to alternative data partitions and network initializations. For each seed, the complete ANN modeling procedure was repeated. Performance across the repeated runs was summarized using the mean and standard deviation of R^2 and RMSE for training, validation, and testing subset. This procedure was used to determine whether the predictive performance of the selected model was maintained across different random partitions rather than arising from a single favorable split.

Repeated holdout validation evaluates model stability within the pooled multispecies dataset but does not constitute validation on an entirely unseen species. Because the available species-level sample sizes were small and unequal, species-wise validation was reserved for future studies using larger and more balanced datasets. Accordingly, the reported performance should be interpreted within the geometric and physical domain represented by the five investigated species.

3.7 Correlation Analysis

Pearson correlation analysis was performed using the original pooled experimental observations to examine the linear relationships among the six ANN input variables: OD, T, MC, D, T/OD, and D×T. The original observations were used and the resulting correlation matrix was visualized using a heatmap to identify potential redundancy among the primary and derived predictors and to support the interpretation of the permutation feature importance results.

Correlations involving T/OD and D×T were expected because these variables were mathematically derived from the directly measured predictors. The correlation analysis was therefore used to evaluate the degree of shared information among the model inputs rather than to establish causal relationships or automatically exclude correlated variables from ANN development.

3.8 Permutation Feature Importance

Permutation feature importance (PFI) was performed to evaluate the relative contribution of each input variable to the predictions of the optimized ANN [22]. Each predictor was randomly permuted while the remaining variables and trained network were kept unchanged. The resulting change in prediction error relative to the original model was used as the importance measure, and the scores were normalized to facilitate comparison among predictors. Because several primary and derived variables were correlated, PFI was interpreted as a model-dependent measure of predictor contribution rather than evidence of an independent or causal relationships with bending strength.

4. RESULTS AND DISCUSSION

4.1 Observed Material Properties and Failure Modes

The observed geometric and physical properties and bending strength of four species were summarized in Tables 1-4. Differences were observed among the species in outer diameter, wall thickness, moisture content, density, and bending strength, illustrating the heterogeneous nature of the pooled experimental dataset. Mean bending strength ranged from 64.08 MPa for *Bambusa vulgaris* to 84.08 MPa for *Guadua angustifolia*. *Guadua angustifolia* also exhibited the greatest mean outer diameter and density, while *Bambusa merilliana* has the greatest mean wall thickness. However, these descriptive relationships should not be interpreted as establishing direct causal effects because the geometric and physical properties varied simultaneously among species. The bending strength coefficients of variation ranged from 0.20 to 0.26, demonstrating appreciable within species variability in the investigated samples. This variability supports evaluating a data-driven method capable of representing relationships among multiple geometric and physical parameters.

Table 1. Descriptive Statistics of *Bambusa merilliana*

Property	Mean	SD	COV	Min	Max
OD	79.55	9.16	0.12	64.60	96.67
(mm)					
T (mm)	14.77	2.98	0.20	9.75	21.78
MC (%)	10.08	1.38	0.14	7.35	11.81
D (kg/m ³)	613.65	88.72	0.14	444.72	764.06
Fm	74.46	17.95	0.24	43.77	109.56
(MPa)					

Table 2. Descriptive Statistics of *Bambusa vulgaris*

Property	Mean	SD	COV	Min	Max
OD (mm)	95.19	9.55	0.10	74.83	119.21
T (mm)	9.40	1.61	0.17	6.05	12.96
MC (%)	12.03	3.43	0.28	8.87	22.26
D (kg/ m ³)	730.94	111.21	0.15	485.85	996.21
Fm (MPa)	64.08	16.23	0.25	30.50	114.86

Table 3. Descriptive Statistics of *Dendrocalamus asper*

Property	Mean	SD	COV	Min	Max
OD (mm)	91.01	5.98	0.07	81.75	106.75
T (mm)	7.43	1.39	0.19	5.13	12.50
MC (%)	10.03	0.74	0.07	8.77	12.12
D (kg/ m ³)	671.45	142.82	0.21	452.89	924.71
Fm (MPa)	76.92	19.90	0.26	26.13	109.41

Table 4. Descriptive Statistics of *Guadua angustifolia*

Property	Mean	SD	COV	Min	Max
OD (mm)	115.63	15.31	0.13	82.44	140.85
T (mm)	13.10	3.11	0.24	8.91	19.74
MC (%)	8.85	1.05	0.12	6.04	10.17
D (kg/ m ³)	808.07	88.19	0.11	636.50	965.48
Fm (MPa)	84.08	17.17	0.20	58.24	128.75

Figure 3-6 presents the typical failure modes observed during four-point bending, including longitudinal splitting, bursting of culm wall, and localized crushing beneath the loading points. Longitudinal splitting on the tension side was associated with tensile stresses acting along the outer fibers, while localized crushing resulted from concentrated compressive stresses beneath the loading points. Bursting and extended splitting reflected the combined effects of longitudinal stress state, local geometry, and the orthotropic structure of the bamboo culm. These observations illustrate that failure was not governed by a single visible mechanism across all specimens.

4.2 Estimated Characteristic Bending Strength

Table 5 presents the estimated characteristic bending strengths of the four experimentally investigated species, calculated using the statistical procedure described in ISO 12122-1 [10]. The estimates represent the lower-tail bending

resistance of the corresponding observed species-level distributions. Among the samples, *Guadua angustifolia* produced the highest estimated value of 57.05 MPa, followed by *Bambusa merrilliana* at 47.39 MPa. However, these two species were represented by only 21 and 28 specimens, respectively. Their estimates should therefore be interpreted as preliminary and require confirmation using larger samples before application to formal grading or structural design. The estimated values for *Bambusa vulgaris* and *Dendrocalamus asper* were 39.47 and 38.48 MPa, respectively. Although these species satisfied the adopted minimum sample-size criterion, the reported values remain specific to the sampled materials. Establishment of design values would additionally require compliance with the applicable sampling, grading, and safety requirements. Accordingly, the estimates presented here are used primarily to compare the lower-tail bending-strength behavior of the investigated samples and are not outputs of the ANN model.

Table 5. Estimated Characteristic values

Species	5 th Percentile Characteristic Value (MPa)
<i>Bambusa merrilliana</i>	47.39
<i>Bambusa vulgaris</i>	39.47
<i>Dendrocalamus asper</i>	38.48
<i>Guadua angustifolia</i>	57.05

Note: Estimates for *B. merrilliana* and *G. angustifolia* are based on fewer than 30 specimens and are reported for preliminary comparative purposes only. Additional testing is required before these values can be adopted for grading or structural design.



Fig. 3 Crushing at the support

4.3 ANN Architecture and Hyperparameter Selection

The grid search procedure identified a three-hidden-layer architecture containing 30, 20, and 10

neurons as the optimal ANN configuration. Among the evaluated combinations, this architecture trained using the Levenberg-Marquardt algorithm produced the lowest validation RMSE after the predictions were converted back to MPa. The selected network used hyperbolic tangent sigmoid activation functions in the hidden layers and a linear activation function in the output layer. Table 6 summarizes the final model configuration.



Fig. 4 Longitudinal splitting



Fig. 5 Bursting failure



Fig. 6 Splitting along the bottom fiber

Model selection was based exclusively on validation performance; the testing subset was reserved for evaluating the predictive performance of the selected configuration. The selected 30-20-10 architecture was therefore carried forward for model evaluation, repeated validation, residual analysis, and feature importance assessment.

Table 6. Optimal Hyperparameter settings for ANN Model

Hyperparameter	Optimal Value
Input variables	OD, T, MC, D, T/OD, DxT
Normalization	Min-max normalization to [-1,1]
Train/Validation/Test Split	70% / 15% / 15%
Performance function	MSE
Tuning Criterion	RMSE
Maximum epochs	1000
Maximum validation failures	20
Model Architecture	30-20-10
Training Function	Levenberg-Marquardt (trainlm)
Hidden layer activation function	tansig
Output layer activation function	linear

4.4 ANN Model Performance

Table 7 presents the predictive performance of the optimized ANN across the training, validation, and testing subsets. The model was trained and evaluated using 1200 bootstrap instances generated from the original pooled dataset of 313 experimental observations. The optimized model achieved a testing R^2 of 0.89, RMSE of 6.76 MPa, MAE of 2.79 MPa, and MAPE of 3.08%. These results indicated good agreement between predicted and experimental bending strengths for the selected data.

The training subset produced an RMSE of 2.56 MPa, which was lower than the validation and testing RMSE. The lower training error was expected because the network parameters were optimized using the training instances. The comparable validation and testing errors indicated that model performance was maintained for the two held-out subsets, although these demonstrate robustness should also be examined across alternative data partitions. This consideration was addressed through the repeated validation presented in Section 4.5.

Table 7. Predictive performance of the optimized ANN

Dataset	Specimen	RMSE	MAE	MAPE	R^2
Train	840	2.56	1.41	1.62	0.98
Validation	180	6.84	2.70	3.05	0.87
Test	180	6.76	2.79	3.08	0.89

To contextualize the added predictive value of the nonlinear model, an MLR model was developed using the same six predictors and corresponding data partition. The MLR produced a testing R^2 of 0.38, compared with 0.89 for the optimized ANN. The lower MLR performance indicates that a simple additive linear model provided limited predictive accuracy for the investigated pooled dataset. In contrast, the improved ANN performance suggests that nonlinear relationships and interactions among the selected parameters contributed to strength prediction.

4.5 Repeated Validation of the ANN Model

Repeated holdout validation was conducted using three random seeds to determine how the ANN performance varied across alternative data partitions and network initializations. As summarized in Table 8, the model achieved a mean testing R^2 of 0.807 ± 0.094 and mean testing RMSE of 8.57 ± 2.76 MPa.

The variation among repeated runs indicates that model performance was influenced to some extent by the selected data partition, although the model maintained useful predictive capability across the evaluated partitions. The single-partition testing result of $R^2 = 0.89$ and RMSE = 6.76 MPa therefore represents one selected model outcome, while the repeated-validation results provide a broader estimate of expected performance within the available pooled dataset.

These findings support the predictive potential of the ANN within the represented material domain but do not demonstrate generalization to an entirely unseen species. Repeated holdout validation evaluates stability across random partitions of the pooled dataset, whereas species-wise validation would require larger and more balanced species-level samples. Leave-one-species-out validation is therefore recommended for future studies with expanded datasets.

4.6 Predicted vs. Observed Bending Strength

Figures 7-9 compares the ANN-predicted and observed bending strengths for training, validation,

and testing subsets. The training predictions were closely distributed around the 1:1 equality line, consistent with the lower training RMSE and higher R^2 . The validation and testing subsets exhibited greater scatter, particularly among specimens with higher bending strengths, indicating that prediction errors increased for some observations outside the central strength range. Nevertheless, the validation and testing predictions generally followed the equality line across the observed bending strength range. The testing subset demonstrated good agreement between predicted and observed values within the represented data. The remaining scatter reflects prediction uncertainty associated with the measured inputs and material variation not fully represented by the model.

Table 8. Repeated validation summary

Metric	Mean $\pm$ SD
Training R^2	0.98 ± 0.017
Validation R^2	0.913 ± 0.039
Testing R^2	0.807 ± 0.094
Training RMSE	2.59 ± 1.52 MPa
Validation RMSE	5.52 ± 1.21 MPa
Testing RMSE	8.57 ± 2.76 MPa

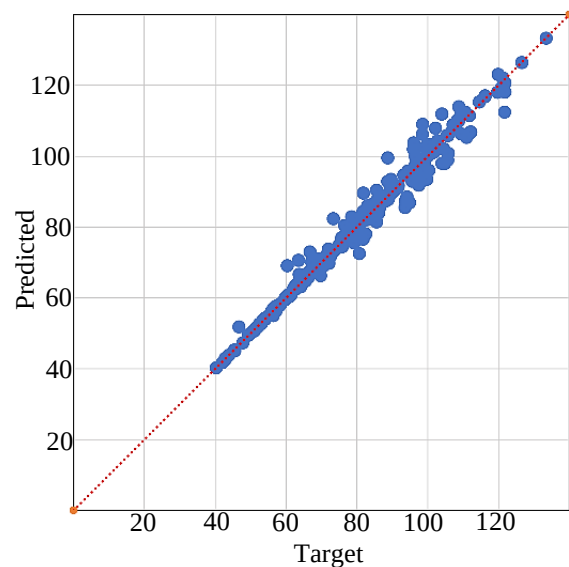


Fig. 7 Predicted vs Target Experimental Bending Strength using Training subset

4.7 Residual Analysis

Residual analysis was performed to examine the magnitude and distribution of the ANN prediction errors. The residual for each observation was

calculated as $e_i = f_{m,i} - f_{m,i,pred}$ where $f_{m,i}$ is the observed bending strength and $f_{m,i,pred}$ is the corresponding ANN prediction. Figure 10 presents the testing-subset residuals plotted against the predicted bending strengths.

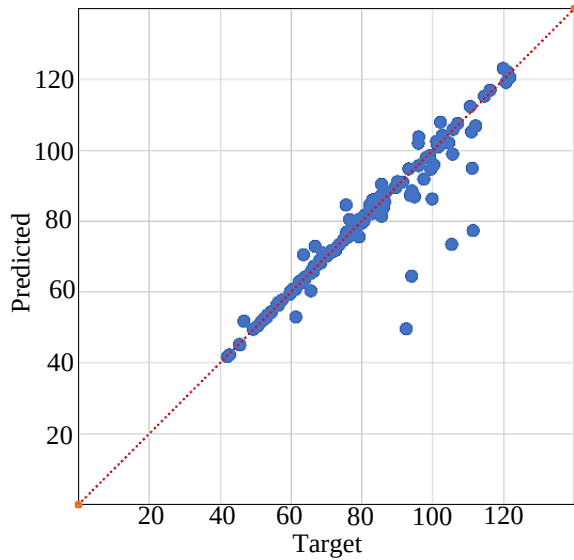


Fig. 8 Predicted vs Target Experimental Bending Strength using Validation subset

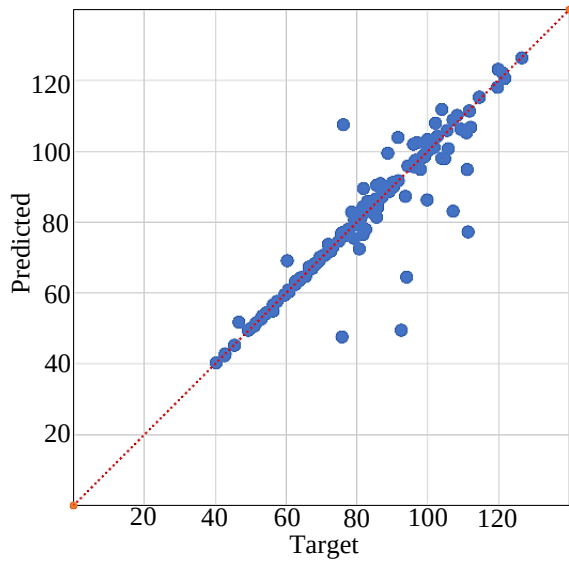


Fig. 9 Predicted vs Target Experimental Bending Strength using Testing subset

Most residuals were concentrated near zero without a clear systematic trend across the predicted strength range, suggesting limited systematic overprediction or underprediction. However, several observations exhibited comparatively large positive and negative residuals, particularly within the middle-to-high strength range. These errors indicate

that the selected geometric and physical predictors did not fully explain the bending strength variation of all specimens. The larger residuals may reflect natural material variability and the influence of unmeasured factors. Because some factors were not included as model inputs, their individual effects cannot be confirmed from the present analysis. The residual pattern therefore supports interpreting the ANN as a preliminary prediction model rather than a replacement for experimental testing.

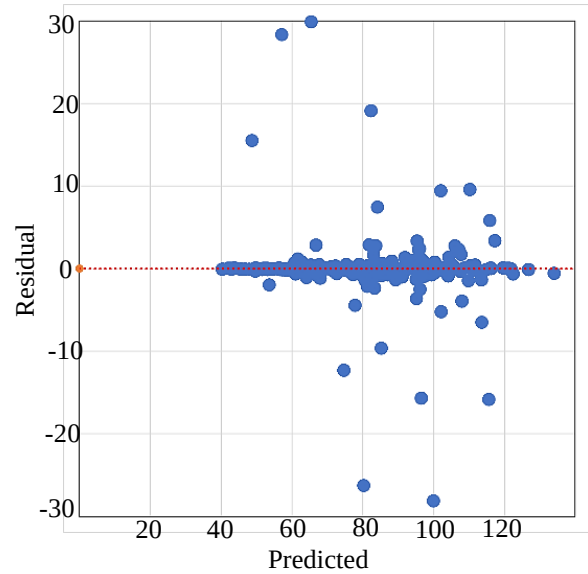


Fig. 10 Residuals between observed and ANN-predicted bending strength using testing subset

4.8 Correlation Analysis

Figure 11 presents the Pearson correlation matrix for the six input variables using the original 313 experimental observations. Strong positive correlations were observed between T and T/OD with $r = 0.902$, between T and $D \times T$ with $r = 0.849$. A moderate positive correlation was also observed between T/OD and $D \times T$ with $r = 0.69$. These relationships were expected because wall thickness is mathematically included in both derived variables. The OD exhibited a weak negative correlation with T/OD and moderate positive correlation with $D \times T$. MC showed only weak relationships with other predictors, with absolute correlation coefficients below 0.16. The correlation matrix therefore indicates that some predictors contain shared information, particularly T , T/OD , and $D \times T$, while other variables contribute relatively distinct geometric or physical information.

The correlated variables were retained because T/OD and $D \times T$ represent physically interpretable geometric and material-geometry descriptors.

However, their correlations mean that their individual feature-importance scores cannot be interpreted independently. The correlation analysis was therefore used to contextualize the permutation feature importance results rather than to establish causal relationships or automatically remove predictors from the ANN. Figure 8 presents the Pearson correlation matrix among the geometric and physical input variables used for ANN model development.

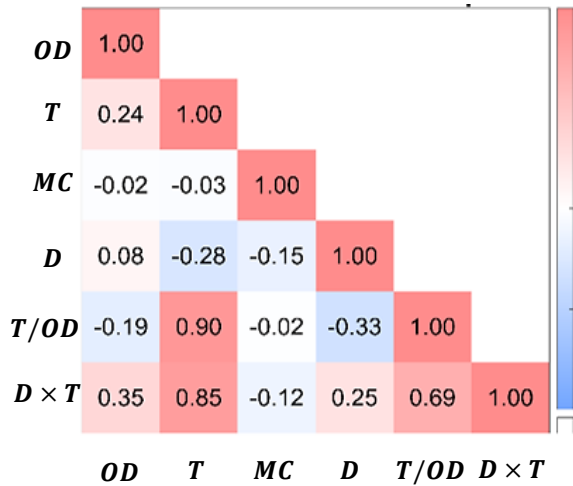


Fig. 11 Pearson correlation heatmap among the input variables used in the ANN model

4.9 Feature Importance Analysis

Figure 12 presents the normalized permutation feature importance (PFI) scores for the optimized ANN. T produced the highest importance score, indicating that permutation of this variable caused greatest deterioration in model performance, whereas OD, MC, and T/OD produced comparatively lower scores.

The higher importance assigned to wall thickness is mechanically plausible because wall thickness contributes to culm cross-sectional geometry and bending resistance. However, this result should not be interpreted as evidence that wall thickness independently governs bending strength. As demonstrated by the correlation analysis, T was strongly correlated with both T/OD and D x T. Consequently, the model may distribute shared predictive information unevenly among these correlated variables, resulting in high importance for one predictor and lower apparent importance for another.

In particular, the low PFI score of T/OD does not necessarily indicate that relative wall thickness lacks mechanical relevance. Its strong correlation with T suggests that much of its predictive information may

already be represented by wall thickness. Similarly, the moderate importance of D x T indicates that the trained model used information contained in the combined material-geometry descriptor, but does it not demonstrate that the derived variable independently improved model performance.

PFI quantifies the dependence of the trained ANN on each predictor under the evaluated dataset and model configuration. The scores are therefore model-dependent and should not be interpreted as causal effects or definitive rankings of the physical factors governing bamboo bending strength.

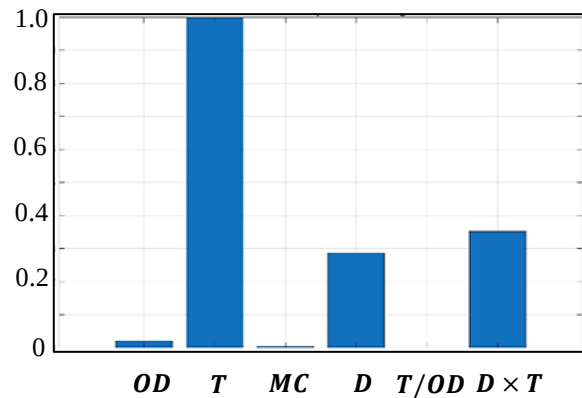


Fig. 12 Normalized Feature Importance Ranking

4.10 Comparison with Previous Studies

The mean bending strengths of the four experimentally investigated species ranged from 64.08 to 84.08 MPa, with coefficients of variation between 0.20 and 0.26. Cacanando et al. reported a mean bending strength of approximately 88 MPa and coefficient of variation of 0.23 for *Bambusa blumeana* [13]. Correal et al. similarly reported a mean bending strength of approximately 83 MPa and a coefficient of variation of 0.25 for *Guadua angustifolia*, which were comparable to the corresponding values obtained in the present study [28]. These comparisons indicate that the observed strength magnitudes and variability fall within ranges reported for comparable bamboo species which provides contextual support for the plausibility of the present experimental results.

Previous studies also provide methodological context for predicting bamboo properties from measurable characteristics to infer mechanical performance. Correal et al. pooled experimental data from two laboratories and applied machine learning method to estimate mean mechanical properties of *Guadua angustifolia* [28]. Their results demonstrated the potential of culm geometry and physical properties for mechanical property inference and structural grading. In this study five

Philippine species were pooled to predict strength. Muhammad and Orejudos applied machine learning models, including ANN, to predict compression, tension, and shear strengths of *Bambusa blumeana* [29]. These studies demonstrated that data-driven methods have been applied to bamboo mechanical property prediction. The present study extends this approach to bending strength prediction using pooled dataset of five Philippine species.

4.11 Engineering Implications

The developed ANN may serve as a preliminary screening tool for estimating bamboo bending strength from readily measurable geometric and physical properties. Its inputs—outer diameter, wall thickness, moisture content, density, thickness-to-diameter ratio, and density–thickness product—can be obtained without conducting destructive bending tests. The model may therefore assist researchers, producers, and engineers in comparing specimens, identifying potentially suitable culms for further testing, and prioritizing materials during preliminary characterization.

The ANN predictions represent specimen-level estimates of bending strength and should not be interpreted as characteristic or design values. Formal material grading and structural design still require representative experimental testing, statistically established characteristic properties, and application of the design provisions and material safety factors prescribed in ISO 22156 [9]. Accordingly, the proposed model is intended to complement, rather than replace, standardized mechanical testing and code-based structural design.

Within these limitations, the ANN may help reduce the number of specimens requiring destructive testing during preliminary screening and assist in planning more focused experimental programs. However, its applicability is limited to bamboo specimens whose geometric and physical properties fall within the domain represented by the five-species pooled dataset. Because all five species were represented during model development, the present results do not establish predictive performance for an entirely unseen species. Future studies should expand the dataset using larger and more balanced species-level samples and conduct leave-one-species-out or independent external validation before applying the model to other bamboo species or geographic sources.

5. CONCLUSION

This study reported standardized four-point bending-test data for four Philippine bamboo species

and developed an artificial neural network (ANN) model for predicting bending strength from readily measurable geometric and physical properties. The experimental observations obtained following ISO 22157:2019 were combined with methodologically compatible published data for one additional species, producing a pooled multispecies dataset of 313 specimens. Without using species identity as an input, the optimized ANN achieved a testing R^2 of 0.89, RMSE of 6.76 MPa, and MAPE of 3.08% for the selected data partition. The ANN also outperformed the multiple linear regression baseline, which achieved a testing R^2 of 0.38, indicating the added predictive value of the nonlinear modeling approach for the investigated dataset.

Repeated holdout validation produced a mean testing R^2 of 0.807 ± 0.094 and RMSE of 8.57 ± 2.76 MPa. These results demonstrate that the ANN generally retained predictive capability across alternative data partitions, although the observed variability indicates some sensitivity to partitioning and network initialization. Permutation feature importance, interpreted together with the Pearson correlation analysis, showed that the trained ANN relied most strongly on wall thickness. The comparatively low importance of the thickness-to-diameter ratio was associated with its strong correlation with wall thickness and should not be interpreted as evidence that relative wall thickness lacks mechanical relevance. These importance results are model-dependent and do not establish independent causal effects.

The model may support preliminary specimen screening and bending-strength estimation using measurements of culm geometry, moisture content, and density. However, its predictions represent specimen-level strength estimates and should not replace standardized mechanical testing, formally established characteristic properties, or the design procedures prescribed in ISO 22156:2021. The estimated characteristic values reported for *Bambusa merrilliana* and *Guadua angustifolia* should also be interpreted as preliminary because these species were represented by fewer than 30 specimens.

The applicability of the ANN is limited to bamboo specimens whose geometric and physical characteristics fall within the material domain represented by the five-species pooled dataset. Because all species were represented during model development, the present evaluation does not establish generalization to an entirely unseen species. Future studies should incorporate larger and more balanced species-level samples, broader geographic sources, and additional descriptors such as culm position, node condition, fiber distribution,

and specimen age. Leave-one-species-out and independent external validation should then be performed to evaluate generalization beyond the present material domain. Additional explainability methods may also complement permutation feature importance when sufficiently large datasets become available.

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