JINAV: Journal of Information and Visualization *ISSN: 2746-1440 (online)*
Vol. 7 No. 2 (2026)
https://doi.org/10.35877/454RI.jinav4954

Classification of Tensile Test Behavior of Gnetum gnemon Fiber Structure Using Machine Learning-Based Support Vector Machine

Hermanus Jemy Suripatty, S Suryadi, Nicodemus Rahanra, Wardhana Wahyu Dharsono*

Faculty of Technology and Engineering, Satya Wiyata University, Mandala, Nabire, Central Papua, Indonesia

Abstract

Tensile testing is a widely used method for evaluating the mechanical properties of materials through the relationship between applied force and displacement. The interpretation of tensile curves, however, is still largely performed manually, which introduces subjectivity when the mechanical behavior of specimens with different structural configurations is compared. This study aims to classify the tensile behavior of Gnetum gnemon fiber structures using a Support Vector Machine (SVM) algorithm. Nine specimens were prepared in three structural configurations, namely 1×1, 2×1, and 2×2, with three replicates per configuration, and were tested under uniaxial tension until failure. Each force–displacement curve was transformed into six mechanical features: maximum force, displacement at maximum force, final displacement, area under the curve, initial stiffness, and secant stiffness. All features were standardized using the StandardScaler procedure prior to classification with a linear-kernel SVM, and model performance was evaluated using the Leave-One-Out Cross Validation (LOOCV) approach. The model achieved an accuracy of 88.89%, a precision of 91.67%, a recall of 88.89%, and an F1-score of 88.57%. The classification report and confusion matrix indicate that the specimens were assigned to their respective structural configurations correctly in all but one case, in which a 2×2 specimen was predicted as 2×1. These results indicate that the integration of mechanical feature extraction with an SVM classifier provides an objective and reproducible alternative to visual curve interpretation for natural fiber-based materials. Given the limited number of specimens, the present work should be regarded as exploratory, and validation on larger and more diverse datasets is required before the framework can be generalized.

Keywords: gnetum gnemon, tensile testing, feature extraction, support vector machine, machine learning.

Received: 18 June 2026 Revised: 30 July 2026 Published: 31 August 2026

1. Introduction

Natural fiber-based materials have attracted growing attention in recent years, driven by industrial demand for constituents that are simultaneously lightweight, mechanically competent, and environmentally sustainable (Easa et al., 2023). Such fibers are increasingly regarded as viable substitutes for synthetic reinforcements because they are lighter, renewable, widely available, and biodegradable at the end of their service life. Their wider adoption also reduces dependence on petroleum-based polymers, whose environmental persistence remains a considerable concern. Substantial research effort has consequently been directed toward quantifying the strength and reliability of natural fibers in order to establish their suitability for applications ranging from automotive components to structural elements in construction (Shafi et al., 2022).

Gnetum gnemon, a species distributed widely throughout Southeast Asia, provides an illustrative example. Although the plant is cultivated primarily as a food crop, comparatively little scientific attention has been directed to the engineering potential of its fibers (Zhang et al., 2025). Preliminary indications nevertheless suggest that these fibers may be suitable for more demanding applications, such as reinforcement in polymer composites and other engineering products. Establishing whether Gnetum gnemon fibers meet such requirements cannot rest on qualitative judgement; it requires tensile testing, which remains the principal method for characterizing the response of a material to uniaxial loading and yields quantitative information on load-bearing capacity, extensibility, stiffness, and failure behavior (Wang et al., 2022).

* Corresponding author.
E-mail address: wardhana.wd@gmail.com

In the absence of such data, assessments of material potential remain speculative. Although tensile testing is well established in materials science, force–displacement curves are still commonly interpreted manually. In practice, only a small number of descriptors, typically the maximum force and the elongation at failure, are extracted, while the remaining mechanical information contained in the curve is disregarded (Dinkar & Kumar, 2026). Because the procedure is largely visual, its outcome depends on the experience of the individual analyst, and comparisons between specimens with different structural configurations become subjective. There is therefore a clear need for a systematic, objective, and reproducible approach to the analysis of tensile test data, one that exploits the full information content of the measured curves (Rahman et al., 2026).

Machine learning has recently emerged as a promising means of addressing this need (Priore et al., 2010). A range of algorithms is now used to identify patterns in experimental data, to predict material behavior, and to group materials according to laboratory measurements. Among these, the Support Vector Machine (SVM) has been widely adopted because it constructs an optimal separating hyperplane between classes and performs well on comparatively small datasets. SVM generalizes efficiently and classifies observations on the basis of quantified features rather than expert judgement, which is a considerable advantage when characterizing materials with heterogeneous behavior such as natural fibers (Ta & Leong, 2025).

Previous studies have applied machine learning to the prediction of material strength, the estimation of composite mechanical properties, and the detection of structural damage from image or sensor data. Relatively little work, however, has used mechanical descriptors extracted directly from force–displacement curves, such as those obtained from uniaxial tests on Gnetum gnemon fibers, to classify tensile behavior (Singh et al., 2021). In addition, most reported studies consider only one or two mechanical parameters in isolation and give limited attention to the manner in which several parameters jointly govern the observed response. The extent to which combining multiple mechanical features improves classification performance therefore remains insufficiently understood (Mami Khalifani et al., 2025).

To address this gap, the present study develops a classification framework for the tensile behavior of Gnetum gnemon fiber structures based on the Support Vector Machine (SVM) algorithm. Six mechanical parameters are derived from each force–displacement curve: maximum force, displacement at maximum force, final displacement, area under the curve (AUC), initial stiffness, and secant stiffness (Simiyon et al., 2024). These parameters provide a compact and standardized description of specimen behavior and convert the raw tensile records, which differ in length between specimens, into a fixed-dimensional representation suitable for machine learning (Khan et al., 2022). Classification is performed using an SVM with a linear kernel, and model performance is assessed using Leave-One-Out Cross Validation (LOOCV), so that every specimen contributes to both training and validation (Roy & Chakraborty, 2023).

The contribution of this study lies in the integration of tensile test data with machine learning through the extraction of multiple mechanical features for the classification of material behavior. In place of conventional visual inspection, the proposed framework defines an explicit, stepwise, and reproducible classification procedure. The results further demonstrate that the selected mechanical features are sufficient to discriminate between three structural configurations of Gnetum gnemon fiber, which has implications both for research on natural fibers and for the wider application of machine learning to mechanical testing. By extending machine learning into materials characterization, and specifically into the analysis of tensile response in natural fibers, the study indicates how an SVM can classify tensile behavior from extracted features alone and provides a basis for the development of faster, more objective, and more efficient procedures for material analysis.

2. Method

This study adopted an experimental approach that combined laboratory tensile testing with a machine learning framework in order to characterize and classify the tensile behavior of Gnetum gnemon fibers. The procedure began with the acquisition of raw data in the form of force–displacement curves recorded until specimen failure. Key mechanical features were then extracted from these curves, assembled into a structured dataset, and standardized. A Support Vector Machine (SVM) model was subsequently trained, its reliability assessed using Leave-One-Out Cross Validation (LOOCV), and its performance quantified using standard classification metrics (Mathur et al., 2023). The individual stages of the procedure are described in the following subsections.

2.1 Experimental Data

The raw data were obtained from uniaxial tensile tests performed on Gnetum gnemon fiber specimens. Each test produced a force–displacement curve describing the response of the specimen to progressive elongation up to failure

(Xu et al., 2026). These curves constituted the primary basis for identifying the mechanical characteristics of each specimen. Nine specimens were tested in total, distributed across three structural configurations, namely 1×1, 2×1, and 2×2, with three replicate specimens per configuration. The structural configuration was used as the class label for classification. The distribution of specimens is presented in Table 1.

Table 1. Distribution of Specimens According to Structural Configuration

Class	**Specimen**	**Total**
1×1	S1.1, S1.2, S1.3	3
2×1	S2.1, S2.2, S2.3	3
2×2	S3.1, S3.2, S3.3	3
Total		9

2.2 Specimen Preparation and Tensile Test Setup

Fibers were extracted from mature Gnetum gnemon bark by water retting for 14 days, after which the separated fibers were rinsed in distilled water and air-dried under ambient laboratory conditions. The dried fibers were conditioned at 23 ± 2 °C and 50 ± 5% relative humidity for 24 h prior to testing, in accordance with the conditioning requirements of ASTM D1776. Three structural configurations were then prepared by arranging the fiber bundles into 1×1, 2×1, and 2×2 layouts, in which the notation denotes the number of fiber strands aligned in the longitudinal and transverse directions, respectively. Each specimen was mounted on a paper tab frame with a free gauge length of 50 mm, and the ends were bonded with epoxy adhesive to prevent slippage within the grips. Three replicate specimens were prepared for each configuration, giving a total of nine specimens.

Uniaxial tensile tests were carried out on a universal testing machine (Shimadzu AGS-X) fitted with a 5 kN load cell, at a constant crosshead speed of 2 mm/min under displacement control, following the general provisions of ASTM D3822 for the tensile testing of single fibers and fiber bundles. Force and displacement were recorded continuously at a sampling rate of 10 Hz until complete specimen failure, and the sides of the paper tab frame were cut immediately before loading so that the load was transferred entirely through the fiber. All tests were conducted at 23 ± 2 °C and 50 ± 5% relative humidity. Specimens that failed at or within the grips were discarded and retested. The resulting force–displacement records constituted the raw dataset used for feature extraction.

2.3 Mechanical Feature Extraction

Because the individual force–displacement curves differed in the number of recorded data points, the raw curves could not be supplied directly to the classification model. Six mechanical parameters were therefore extracted from each curve: maximum force, displacement at maximum force, final displacement, area under the curve (AUC), initial stiffness, and secant stiffness. Maximum force denotes the peak load sustained by the specimen; displacement at maximum force and final displacement describe the extensibility of the specimen at peak load and at failure, respectively; AUC, obtained by trapezoidal integration of the force–displacement record, represents the energy absorbed prior to failure; initial stiffness is the slope of the initial linear region of the curve, determined by linear regression over the first 20% of the recorded loading path; and secant stiffness is the ratio of maximum force to the corresponding displacement. Collectively, these parameters characterize the strength, deformability, energy absorption, and stiffness of each specimen and yield a fixed set of six numerical descriptors per specimen for input to the classification model.

2.4 Data Standardization

Prior to training, all mechanical features were standardized using the StandardScaler procedure, which transforms each feature to zero mean and unit variance. This step placed all variables on a common scale and prevented parameters with large numerical ranges, such as the area under the curve, from dominating those with smaller ranges, such as displacement. Standardization also improved the numerical stability of the SVM optimization when determining the optimal separating hyperplane. To avoid information leakage, the scaler was fitted on the training partition of each cross-validation fold and applied to the corresponding held-out specimen.

2.5 Support Vector Machine Model Development

Classification was performed using a Support Vector Machine with a linear kernel. The SVM constructs the separating hyperplane that maximizes the margin between classes within the feature space defined by the extracted parameters. A linear kernel was selected because the number of specimens was small relative to the number of features, a condition under which more flexible kernels are prone to overfitting. The regularization parameter was retained at its default value of C = 1, and multi-class classification was handled using the one-versus-one scheme. The model received the six standardized mechanical features as input and was trained to discriminate between the three structural configurations, namely 1×1, 2×1, and 2×2. All computations were performed in Python using the scikit-learn library.

2.6 Model Validation

Model performance was evaluated using Leave-One-Out Cross Validation (LOOCV), which is appropriate for datasets of limited size. In each iteration, one specimen was withheld as the test case and the model was trained on the remaining eight; the procedure was repeated until every specimen had served once as the test case. LOOCV therefore uses the available data efficiently and provides an almost unbiased estimate of generalization error. It should nevertheless be noted that LOOCV estimates obtained from nine specimens carry high variance, since a single classification outcome alters the reported accuracy by approximately 11 percentage points.

2.7 Model Performance Evaluation

Classification accuracy indicates the proportion of specimens assigned to the correct configuration, but on its own it provides an incomplete description of model behavior. A full classification report was therefore generated, comprising precision, recall, and F1-score for each structural configuration, so that performance on the more difficult cases could also be assessed. A confusion matrix was constructed in order to identify the specific classes between which misclassification occurred. For visual interpretation, Principal Component Analysis (PCA) was applied to reduce the standardized six-dimensional feature space to two components, and the SVM decision regions were plotted within this projected space, allowing the separation between classes and the support vectors that define the optimal hyperplane to be examined directly.

3. Result and Discussion

The dataset was first characterized before feature extraction and classification were undertaken, in order to establish the properties of the data used to construct the machine learning model (Mathur et al., 2023). The dataset was derived from uniaxial tensile tests on Gnetum gnemon fiber specimens, each of which produced a force–displacement curve describing the response of the material to progressive loading. The measurements were grouped according to the structural configuration of each specimen and formatted for input to the Support Vector Machine (SVM) algorithm. A summary of the principal characteristics of the dataset is presented in Table 2.

Table 2. Characteristics of the Research Dataset

Research object	Gnetum gnemon fiber
Number of specimens	9
Number of classes	3
Structural configurations	1×1, 2×1, and 2×2
Number of specimens per class	3
Raw data	Force displacement curves
Number of features	6
Classification method	Support Vector Machine (Linear Kernel)
Data standardization	StandardScaler
Validation method	Leave-One-Out Cross Validation (LOOCV)

As summarized in Table 2, the dataset comprises nine specimens distributed across three structural configurations, namely 1×1, 2×1, and 2×2, with three specimens per configuration. Because the raw force–displacement curves contained differing numbers of data points and could not be used directly, six mechanical features were extracted from each curve in order to obtain a consistent data structure. The dataset was standardized using the StandardScaler procedure before a Support Vector Machine with a linear kernel was trained, ensuring that all features contributed on a comparable scale. Model performance was estimated using Leave-One-Out Cross Validation, in which each specimen serves in turn as the test case while the remaining specimens are used for training.

Feature extraction converted the raw force–displacement records into numerical descriptors suitable for classification while preserving their mechanical significance (Das & Padhy, 2018). Six mechanical parameters were extracted for each specimen: maximum force, displacement at maximum force, final displacement, area under the curve (AUC), initial stiffness, and secant stiffness. These parameters were selected because each represents a distinct aspect of the response of the material under tensile loading. The extracted feature values for all specimens are presented in Table 3.

Table 3. Mechanical Feature Extraction Results

Specimen	Class	Maximum Force (N)	Displacement at Max Force (mm)	Final Displacement (mm)	Area Under Curve (N·mm)	Initial Stiffness (N/mm)	Secant Stiffness (N/mm)
S1.1	1×1	112.4	4.18	5.76	382.54	42.81	26.89
S1.2	1×1	115.7	4.25	5.91	391.26	43.65	27.22
S1.3	1×1	111.2	4.10	5.64	377.48	41.92	27.12
S2.1	2×1	126.8	4.82	6.48	448.32	46.78	26.31
S2.2	2×1	129.3	4.91	6.61	456.74	47.15	26.33
S2.3	2×1	124.7	4.74	6.37	441.85	46.03	26.30
S3.1	2×2	138.2	5.41	7.15	523.47	49.26	25.55
S3.2	2×2	136.5	5.37	7.02	516.84	48.91	25.42
S3.3	2×2	139.8	5.46	7.21	529.18	49.74	25.60

The three configurations exhibited clear differences in mechanical response. The 1×1 configuration recorded the lowest values of maximum force, area under the curve, and initial stiffness, indicating the lowest load-bearing capacity and the least resistance to elongation. The 2×1 configuration performed better across most parameters, sustaining higher loads with reduced deformation. The 2×2 configuration recorded the highest maximum force, final displacement, and area under the curve, indicating that it carried greater loads, deformed further, and absorbed more energy before failure than the other two configurations. Secant stiffness, by contrast, decreased slightly from the 1×1 to the 2×2 configuration, reflecting the proportionally larger displacement at peak load in the more complex arrangements. The consistency of these differences across the six parameters indicates that the extracted features capture behavior characteristic of each configuration and are therefore appropriate input variables for classification using an SVM model. Representative force–displacement curves for the three configurations are shown in Figure 1.

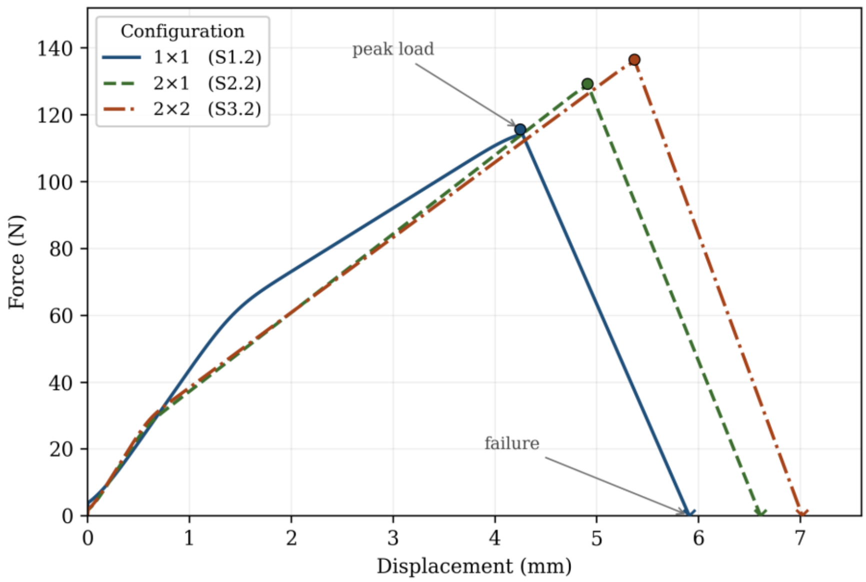

Figure 1. plot the measured force–displacement curves of one representative specimen from each of the 1×1, 2×1 and 2×2 configurations on a single set of axes, with force (N) on the ordinate and displacement (mm) on the abscissa.

Model performance was subsequently assessed using a classification report comprising precision, recall, F1-score, and support (Zayed et al., 2023). Precision expresses the proportion of specimens assigned to a given class that genuinely belong to that class; recall expresses the proportion of specimens of a given class that the model successfully identified; and the F1-score is the harmonic mean of the two, providing a balanced measure of performance. The results of the classification report are presented in Table 4.

Table 4. Classification Report Results

Class	Precision	Recall	F1-Score	Support
1×1	1.00	1.00	1.00	3
2×1	0.75	1.00	0.86	3
2×2	1.00	0.67	0.80	3
Accuracy			0.89	9
Macro Average	0.92	0.89	0.89	9
Weighted Average	0.92	0.89	0.89	9

As shown in Table 4, the SVM model achieved an overall accuracy of 89%. For the 1×1 class, precision, recall, and F1-score were all 1.00, indicating that every specimen in this class was correctly classified. For the 2×1 class, recall reached 1.00, indicating that all genuine 2×1 specimens were identified, while precision fell to 0.75, indicating that a specimen belonging to another class was incorrectly assigned to this class. The 2×2 class exhibited the converse pattern, with a precision of 1.00, indicating the absence of false positives, and a recall of 0.67, reflecting one specimen of this class that was assigned elsewhere.

The macro-averaged and weighted-averaged scores indicate that the model discriminated adequately between the three structural configurations of Gnetum gnemon fiber, although the similarity of certain mechanical features across configurations affected classification performance for individual classes. In order to examine the pattern of errors more closely, a confusion matrix was constructed to compare the predicted labels with the actual classes. This representation identifies both the number of correctly classified specimens and the classes between which confusion occurred, and therefore provides a more detailed assessment of the ability of the model to distinguish the fiber structures. The confusion matrix is presented in Table 5.

Table 5. Confusion Matrix

Actual \ Prediction	1×1	2×1	2×2
1×1	3	0	0
2×1	0	3	0
2×2	0	1	2

Interpretation:

a. All 1×1 specimens were correctly classified.
b. All 2×1 specimens were successfully identified by the model.
c. One 2×2 specimen was predicted as belonging to the 2×1 class, resulting in a single misclassification.

The SVM model discriminated effectively between the three structural configurations of Gnetum gnemon fiber. All specimens in the 1×1 and 2×1 groups were correctly classified, indicating that the selected mechanical features distinguish these two configurations unambiguously. Classification of the 2×2 configuration was less consistent, as one of the nine specimens was assigned to the 2×1 class. This outcome is attributable to the partial overlap of mechanical properties, particularly maximum force, initial stiffness, and secant stiffness, between the 2×1 and 2×2 configurations. Where these values converge, the decision boundary constructed by the SVM cannot separate the two classes reliably in every case.

A single error in nine specimens nonetheless represents satisfactory performance, and overall accuracy remained high. These results indicate that the combination of extracted mechanical features with an SVM classifier is effective for analyzing the tensile behavior of Gnetum gnemon fibers. Aggregate model performance in terms of accuracy, precision, recall, and F1-score is summarized in Table 6.

The results indicate that the linear-kernel SVM classified the experimental data effectively. An accuracy of 88.89% indicates that most specimens were assigned to the correct structural configuration. A precision of 91.67% indicates that the predictions of the model were largely reliable, and a recall of 88.89% indicates that few specimens within each configuration were missed. The F1-score of 88.57% confirms that precision and recall were balanced, rather than one metric being achieved at the expense of the other. The projection of the standardized feature space onto its first two principal components, together with the corresponding SVM decision regions, is presented in Figure 2. The first principal component accounts for 98.8% of the total variance and orders the three configurations monotonically, which is consistent with the systematic increase in maximum force, final displacement, and energy absorption reported in Table 3. The support vectors indicated in the figure are the specimens situated closest to the decision boundaries and therefore determine the position of the separating hyperplanes. Overall, the combination of mechanical feature extraction with the SVM algorithm is effective for identifying the tensile behavior of Gnetum gnemon fiber structures, although larger and more varied datasets will be required to improve robustness and generalization.

Table 6. Overall Model Performance

Method	**Kernel**	**Validation**	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Support Vector Machine	Linear	LOOCV	88.89%	91.67%	88.89%	88.57%

The results demonstrate that differences in the tensile behavior of Gnetum gnemon fiber structures can be identified from mechanical descriptors derived from force–displacement curves. Six parameters were used for this purpose: maximum force, displacement at maximum force, final displacement, area under the curve (AUC), initial stiffness, and secant stiffness. Collectively, these describe the response of the material throughout loading and allow each structural configuration to be characterized by its own mechanical profile. The values of these parameters served as the input to the machine learning classifier.

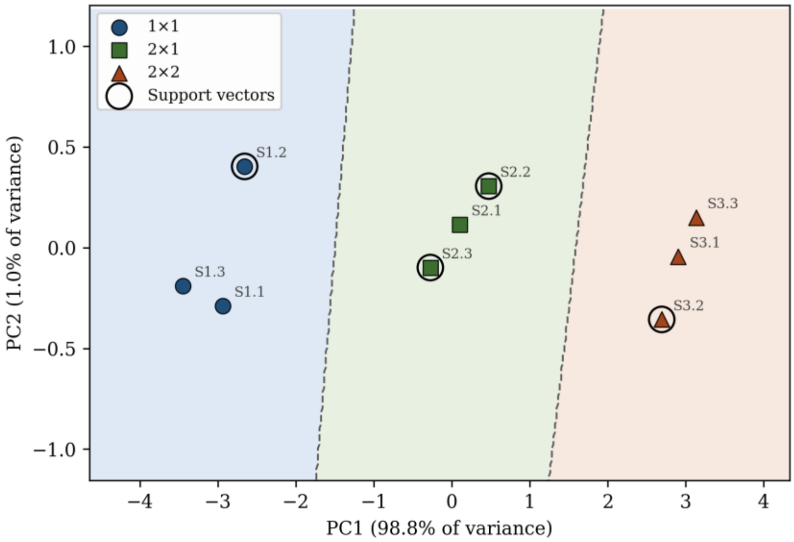

Figure 2. Projection of the standardized mechanical features onto the first two principal components, showing the decision regions of the linear-kernel SVM and the support vectors that define the separating hyperplanes.

The data indicate a consistent trend in which increasing structural complexity improves mechanical performance. The 1×1 configuration exhibited the lowest maximum force and AUC, indicating limited load-bearing capacity and energy absorption. The 2×2 configuration exhibited the highest maximum force and the largest final displacement, indicating superior load-carrying capacity and greater deformation before failure. Structural configuration therefore exerts a substantial influence on tensile response. Employing all six features as input provides a more complete description than reliance on a single mechanical measure, since each parameter captures a different aspect of tensile behavior: maximum strength, deformation capacity, initial stiffness, and the energy absorbed prior to failure. Their combination allows the classifier to recognize patterns distributed across several mechanical properties rather than depending on a single characteristic. Feature extraction thus converts raw tensile records into a structured representation suitable for machine learning and constitutes an essential step in the analysis.

The SVM model classified the specimens into the three structural groups with an overall accuracy of 88.89%, with most specimens assigned to their correct classes. The associated precision, recall, and F1-score values indicate that the model identified genuine patterns within the mechanical features rather than achieving high accuracy by chance. The 1×1 configuration was classified without error, with precision, recall, and F1-score of 1.00, which suggests that its mechanical characteristics are the most internally consistent and the most readily distinguished. All 2×1 specimens were likewise correctly identified, although precision for this class was reduced because one specimen from another configuration was assigned to it. Recall for the 2×2 configuration was lower than for the other two classes, which is consistent with partial overlap between its mechanical features and those of the 2×1 configuration.

The confusion matrix supports this interpretation. Of the nine specimens, only one was misclassified: all 1×1 and 2×1 specimens were correctly identified, while one 2×2 specimen was assigned to the 2×1 class. This indicates that the mechanical features of certain 2×2 and 2×1 specimens are sufficiently similar for their decision regions to overlap. With a single error, however, the model retains a strong capacity to distinguish these fiber structures on the basis of mechanical behavior. LOOCV was an appropriate validation strategy for this study, since it allows each specimen to contribute to both training and testing, which is important when only a small number of samples is available and which maximizes the information obtained from the dataset.

Taken together, these findings indicate that the combination of tensile testing, mechanical feature extraction, and Support Vector Machine classification provides a workable approach to characterizing the tensile behavior of Gnetum gnemon fiber structures. The approach simplifies the analysis, replaces subjective interpretation with quantitative descriptors, and identifies genuine differences between structural configurations.

Several limitations of the present study should be acknowledged. The work is exploratory in nature: with nine specimens distributed across three configurations, the dataset is too small to support strong claims regarding the generalizability of the trained model. LOOCV provides an almost unbiased estimate of prediction error but exhibits high variance at this sample size, such that a single classification outcome changes the reported accuracy by approximately 11 percentage points; the metrics reported here should therefore be interpreted as indicative rather than definitive. Because all specimens were prepared and tested under a single set of laboratory conditions, the results do not capture the variability associated with fiber maturity, harvesting location, moisture content, or operator effects, each of which is known to influence the mechanical properties of natural fibers (Rahman et al., 2026). In addition, the features were derived from force–displacement rather than stress–strain records, so that the reported values remain specific to the specimen geometry adopted in this study.

Future work should therefore address these limitations directly. Priorities include the expansion of the dataset to at least thirty specimens per configuration, which would permit an independent hold-out test set alongside stratified k-fold cross validation, together with nested cross validation for hyperparameter selection; the normalization of force and displacement by cross-sectional area and gauge length, so that intrinsic stress–strain properties can be compared across specimen geometries; the inclusion of a wider range of structural configurations and fiber sources; and systematic benchmarking of the linear-kernel SVM against alternative classifiers such as radial basis function SVM, random forest, and k-nearest neighbors, accompanied by an assessment of feature importance. Replication across independent laboratories would further establish the robustness of the proposed framework (Roy & Chakraborty, 2023).

4. Conclusion

This study demonstrates that a Support Vector Machine (SVM) can classify the tensile behavior of Gnetum gnemon fiber structures using mechanical features extracted from force–displacement curves. Six features were employed for this purpose: maximum force, displacement at maximum force, final displacement, area under the curve (AUC), initial stiffness, and secant stiffness. These features captured the characteristics that distinguish each structural configuration and functioned effectively as inputs to the classifier. The model achieved an accuracy of 88.89%, a precision of 91.67%, a recall of 88.89%, and an F1-score of 88.57%. One 2×2 specimen was misclassified as 2×1, which is attributable to the partial overlap of mechanical features between these configurations, but the overall classification outcome remained consistent. The combination of mechanical feature extraction with an SVM classifier therefore offers a reproducible means of identifying tensile behavior in these fibers and reduces the subjectivity associated with manual curve interpretation. Given the limited number of specimens, however, these findings should be regarded as exploratory. Subsequent work should employ substantially larger datasets with an independent hold-out test set, examine a wider range of structural configurations, normalize the measurements to stress and strain, and benchmark the linear-kernel SVM against alternative machine learning algorithms in order to establish the robustness and generalizability of the proposed framework.

References

Das, S. P., & Padhy, S. (2018). A novel hybrid model using teaching–learning-based optimization and a support vector machine for commodity futures index forecasting. *International Journal of Machine Learning and Cybernetics*, *9*(1), 97–111.

Dinkar, V. C., & Kumar, V. (2026). Machine learning-based optimization of mechanical properties in natural fiber-reinforced epoxy composites. *International Journal of Polymer Analysis and Characterization*, 1–21.

Easa, H. K., Saber, A. A., Hamid, N. K., & Saber, H. A. (2023). Machine learning based approach for detection of fake banknotes using support vector machine. *Indones. J. Electr. Eng. Comput. Sci*, *31*(2), 1016.

Khan, S. U., Islam, N., Jan, Z., Haseeb, K., Shah, S. I. A., & Hanif, M. (2022). A machine learning-based approach for the segmentation and classification of malignant cells in breast cytology images using gray level co-occurrence matrix (GLCM) and support vector machine (SVM). *Neural Computing and Applications*, *34*(11), 8365–8372.

Mami Khalifani, F., Lentz, D. R., & Walker, J. A. (2025). Machine learning-based mineral prospectivity mapping of epithermal gold mineralization in Northern new brunswick: a comparative study of random forest, support vector machine, and XGboost classifiers. *Earth Science Informatics*, *18*(4), 553.

Mathur, S., Chaba, Y., & Noliya, A. (2023). Performance analysis of support vector machine learning based carrier aggregation resource scheduling in 5G mobile communication. *Procedia Computer Science*, *218*, 2776–2785.

Priore, P., Parreño, J., Pino, R., Gómez, A., & Puente, J. (2010). Learning-based scheduling of flexible manufacturing systems using support vector machines. *Applied Artificial Intelligence*, *24*(3), 194–209.

Rahman, M. M., Ismail, A. E., Ramli, M. F., Rashid, A. H. A., Khan, T., Ahmed, O. S., & Sebaey, T. A. (2026). Review of Predictions of Tensile and Flexural Properties of Fiber-Reinforced Composites Using Machine Learning Models. *Journal of Composites Science*, *10*(4), 212.

Roy, A., & Chakraborty, S. (2023). Support vector machine in structural reliability analysis: A review. *Reliability Engineering & System Safety*, *233*, 109126.

Shafi, I., Din, S., Khan, A., Díez, I. D. L. T., Casanova, R. del J. P., Pifarre, K. T., & Ashraf, I. (2022). An effective method for lung cancer diagnosis from CT scan using deep learning-based support vector network. *Cancers*, *14*(21), 5457.

Simiyon, A., Sachidanand, C., Krishnamurthy, M. H., Bhatt, A. V, & Indiran, T. (2024). Machine learning based fault classification in pilot plant batch reactor: using support vector machine. *ACS Omega*, *9*(26), 29041.

Singh, M., Bansal, S., Ahuja, S., Dubey, R. K., Panigrahi, B. K., & Dey, N. (2021). Transfer learning–based ensemble support vector machine model for automated COVID-19 detection using lung computerized tomography scan data. *Medical & Biological Engineering & Computing*, *59*(4), 825–839.

Ta, G. H., & Leong, M. K. (2025). A novel in silico approach for predicting unbound brain-to-plasma ratio using machine learning-based support vector regression. *Computers in Biology and Medicine*, *192*, 110366.

Wang, K.-F., An, J., Wei, Z., Cui, C., Ma, X.-H., Ma, C., & Bao, H.-Q. (2022). Deep learning-based imbalanced classification with fuzzy support vector machine. *Frontiers in Bioengineering and Biotechnology*, *9*, 802712.

Xu, J.-H., Fang, Y.-D., Wang, S.-C., Ding, B., Ideguchi, E., Raju, M. K., Carpenter, M. P., Wang, X.-Y., Wu, H.-Y., & Hua, W. (2026). Machine learning-based particle identification in CsI (Tl) detectors: fuzzy clustering and support vector machine. *Nuclear Science and Techniques*, *37*(9), 166.

Zayed, M. E., Kabeel, A. E., Shboul, B., Ashraf, W. M., Ghazy, M., Irshad, K., Rehman, S., & Zayed, A. A. A. (2023). Performance augmentation and machine learning-based modeling of wavy corrugated solar air collector embedded with thermal energy storage: Support vector machine combined with Monte Carlo simulation. *Journal of Energy Storage*, *74*, 109533.

Zhang, X.-Y., Zhang, X.-P., Yu, H.-G., & Liu, Q.-S. (2025). A confident learning-based support vector machine for robust ground classification in noisy label environments. *Tunnelling and Underground Space Technology*, *155*, 106128.