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# EXPERIMENTAL EVALUATION AND MODERN DATA-DRIVEN PREDICTION FRAMEWORK FOR SUSTAINABLE ACOUSTIC PANELS MANUFACTURED FROM COCONUT FIBRE AND SUGARCANE BAGASSE

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## ABSTRACT

*Agricultural residues provide an attractive route for developing low-cost and environmentally responsible acoustic materials, but their performance is strongly dependent on composition, density, thickness, binder content and acoustic frequency. This study experimentally investigates noise-control panels prepared from coconut fibre, sugarcane bagasse and a combined coconut-fibre/bagasse formulation. The available project dataset reports an initial sound level of 84 dB for all three configurations. The measured levels after panel placement were 66 dB for the combined panel, 70 dB for coconut fibre and 73 dB for bagasse, corresponding to observed reductions of 18, 14 and 11 dB, respectively. The combined formulation therefore produced the highest reduction within the reported test arrangement. Importantly, these measurements represent differences in sound-level readings in the project setup and are not standardized sound absorption coefficients. To advance the work toward a modern Scopus-oriented research contribution, this paper develops a rigorous data-driven prediction framework based on support vector regression (SVR), random forest (RF), extremely randomized trees (Extra Trees), gradient boosting (GB), quadratic response-surface modelling, explainable artificial intelligence (SHAP/permutation importance), and multi-objective optimization. The framework uses material composition, panel thickness, density, binder content and frequency as candidate predictors and sound absorption coefficient or controlled sound-level reduction as the response. Because only three panel-level observations are available in the present source dataset, no artificial ML accuracy values are reported. Instead, a statistically defensible experimental expansion and nested cross-validation protocol are specified. The study consequently provides both a verified experimental baseline and a reproducible pathway for transforming agro-waste acoustic-panel development into a data-driven materials-design problem.*

**Keywords:** Agro-waste, Coconut fibre, Sugarcane bagasse, Acoustic panel, Noise control, Machine learning, SVR, Random forest, Extra Trees, Gradient boosting, Sustainable construction, Sound absorption

## I. INTRODUCTION

Noise pollution is increasingly associated with transportation, construction, industrial equipment, generators and densely occupied urban environments. At the same time, agricultural processing generates large volumes of fibrous residues that require productive end uses. The simultaneous occurrence of these two environmental challenges motivates the development of acoustic materials from renewable and locally available waste resources. The source project investigated coconut fibre and sugarcane bagasse as panel constituents and compared individual and combined configurations. The reported experiment found that the combined panel reduced the measured sound level from 84 to 66 dB, while coconut fibre and bagasse reduced it to 70 and 73 dB, respectively.

Recent research confirms the broader potential of agricultural residues as acoustic materials. Sugarcane bagasse has been investigated using controlled thickness and density, with sound absorption characterized by impedance-tube testing and modelled using physical/statistical approaches. Recent work on agricultural by-products has also emphasized coconut coir, paddy straw, waste paper and controlled density/adhesive content. More recent studies have introduced machine-learning prediction for acoustic materials, demonstrating that RF, SVR variants and neural models can learn nonlinear relationships between structural parameters and acoustic response when sufficiently large datasets are available. These developments suggest a promising next step for agro-waste panels: integrate systematic experimentation with explainable machine learning and optimization rather than relying only on trial-and-error material development.

The novelty proposed in this manuscript is therefore twofold: (i) experimental comparison of coconut fibre, sugarcane bagasse and their combined panel in the available project configuration; and (ii) formulation of a modern, experimentally anchored prediction-and-optimization workflow for future acoustic-panel datasets. The second contribution is deliberately presented as a framework rather than as a fabricated ML result, because the supplied dataset contains only three panel-comparison observations.

## II. RESEARCH GAP AND NOVELTY

### 2.1 Research gap

The source study itself identifies several unresolved variables: frequency-dependent absorption, density, thickness, binder content, durability, moisture resistance, fire behaviour and mechanical properties. In addition, the current experiment uses overall dB readings rather than standardized sound absorption coefficients. These limitations prevent direct comparison with impedance-tube datasets and prevent reliable training of high-capacity machine-learning models.

### 2.2 Proposed novelty

- Hybridization of coconut fibre and sugarcane bagasse as a sustainable acoustic-panel concept.
- Integration of controlled acoustic testing with a multivariable database containing material composition, thickness, density, binder percentage and frequency.
- Benchmarking quadratic response-surface modelling against nonlinear ML models: SVR, RF, Extra Trees and Gradient Boosting.
- Use of explainable ML (SHAP/permutation importance) to identify the dominant material and geometric parameters.
- Use of Bayesian or evolutionary multi-objective optimization to identify panel designs balancing acoustic performance, material cost and sustainability.
- Independent experimental validation of the final optimized panel rather than relying only on training/test statistics.

## III. MATERIALS AND EXPERIMENTAL EVIDENCE

The project used coconut fibre, sugarcane bagasse and a binder/adhesive to fabricate panel specimens. The source document describes collection, cleaning, drying, size preparation, mixing, moulding, compression and drying/curing. The binder is described generally as resin, gum or adhesive; a single standardized formulation is not specified in the available document. Consequently, binder type and dosage must not be reconstructed or assumed in a journal submission without laboratory records.

**Table 1: Measured sound levels before and after panel placement**

| Configuration | Initial level (dB) | With panel (dB) | Observed reduction (dB) | Reduction / initial (%) |
|---|---|---|---|---|
| Combined coconut fibre + bagasse | 84 | 66 | 18 | 21.43 |
| Coconut fibre | 84 | 70 | 14 | 16.67 |
| Sugarcane bagasse | 84 | 73 | 11 | 13.10 |

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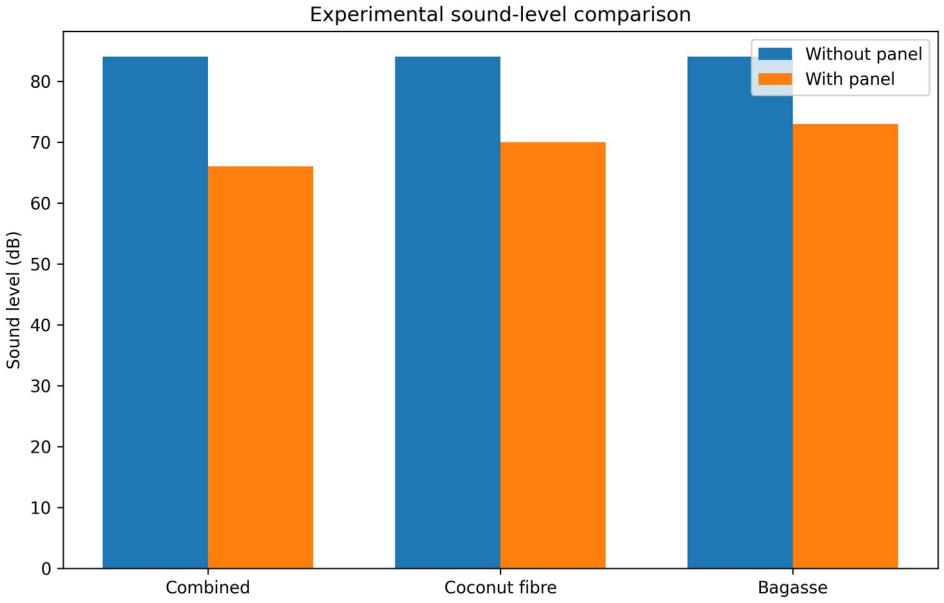



**Figure 1. Comparison of measured sound levels before and after panel placement.**

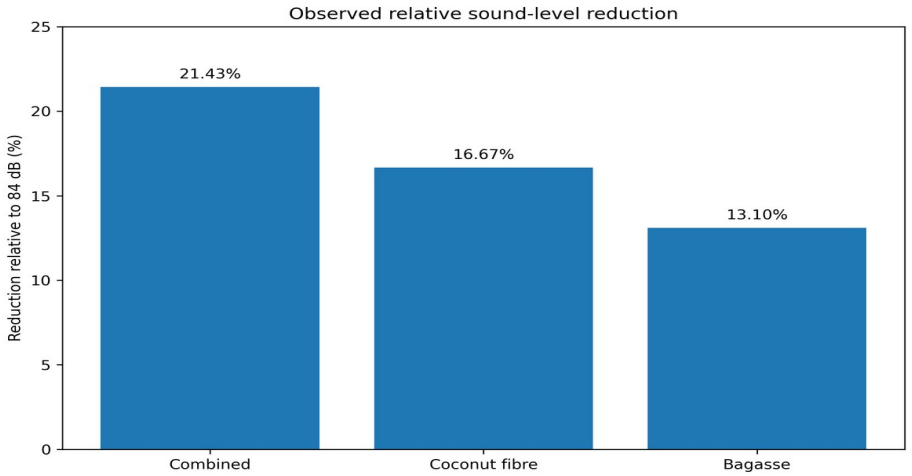



**Figure 2. Observed reduction expressed relative to the common 84 dB initial reading.**

## IV. EXPERIMENTAL METHODOLOGY

The reported procedure consisted of measuring the initial sound level without a panel, inserting the selected panel between the sound source and measurement point, recording the new level and calculating the observed difference using $\Delta L = L_{without} - L_{with}$. The available document reports an enclosed small-scale test arrangement and sound-level meter measurements. For the next stage of publication-quality work, this arrangement should be upgraded or complemented by standardized impedance-tube testing, with repeated specimens and frequency-resolved measurements.

### 4.1 Recommended expanded experimental matrix

A predictive model requires substantially more than three observations. A practical minimum dataset should vary at least five explanatory dimensions: material composition, panel thickness, bulk density, binder percentage and acoustic frequency. Replicate specimens should be included so that experimental variability can be quantified. A frequency-resolved impedance-tube dataset is preferable because sound absorption coefficient is dimensionless and directly comparable across studies.

**Table 2: Recommended expanded experimental matrix**

| Variable | Recommended levels / representation | Role |
|---|---|---|
| Coconut fibre fraction | 0–100 wt.% (continuous) | Material composition |
| Bagasse fraction | 0–100 wt.% (continuous) | Material composition |
| Binder content | At least 3–5 experimentally selected levels | Bonding/porosity control |
| Panel thickness | At least 3–4 levels | Acoustic path length |
| Bulk density | At least 3 levels | Porosity/flow resistance proxy |
| Frequency | e.g., 125–4000 Hz or apparatus range | Acoustic excitation |
| Replicates | ≥3 per selected formulation | Uncertainty and repeatability |

## V. RESULTS OF THE PRESENT EXPERIMENTAL DATASET

The combined panel produced the largest observed reduction, 18 dB, followed by coconut fibre at 14 dB and bagasse at 11 dB. Since the initial reading was the same for all three configurations, the ranking is directly visible within the reported test arrangement. The combined panel achieved a 28.6% larger dB reduction than coconut fibre alone and a 63.6% larger dB reduction than bagasse alone, calculated from the reported reductions. These ratios are descriptive comparisons only; they should not be interpreted as standardized acoustic absorption improvements.

**Table 3: Increase in observed dB reduction**

| Comparison | Increase in observed dB reduction |
|---|---|
| Combined vs. coconut fibre | 28.6% |
| Combined vs. bagasse | 63.6% |
| Coconut fibre vs. bagasse | 27.3% |

The combined-panel result is consistent with the general hypothesis that combining two fibrous constituents can modify the internal structure available for sound interaction. However, the present experiment does not separately measure porosity, tortuosity, airflow resistivity, density, thickness or frequency-dependent absorption. Therefore, a mechanistic claim that the hybrid panel is superior because of a particular pore structure would be premature.

### 5.1 Important acoustic interpretation

The reported 18, 14 and 11 dB values are sound-level differences in the project setup. They are not equivalent to a standardized sound absorption coefficient (α), noise reduction coefficient (NRC), sound absorption average (SAA), or sound transmission loss (TL) unless the relevant standardized test procedure and calculation are performed. This distinction is essential for a high-quality journal submission.

## VI. MODERN PREDICTION METHODOLOGY

The proposed prediction stage treats acoustic performance as a nonlinear function of material composition and physical parameters. Candidate input vector X may be expressed as X = [Coconut fraction, Bagasse fraction, Binder content, Thickness, Density, Frequency]. The target y may be the measured sound absorption coefficient α(f), or, if the same project setup is retained, a controlled sound-level reduction ΔL. The preferred journal-grade target is α(f) obtained from impedance-tube testing.

### 6.1 Quadratic response-surface model

A quadratic model can represent main effects, curvature and pairwise interactions: $y = \beta_0 + \Sigma\beta_i x_i + \Sigma\beta_{ii} x_i^2 + \Sigma\beta_{ij} x_i x_j + \varepsilon$. It provides an interpretable baseline and can identify broad optimum regions when the design space is reasonably sampled.

### 6.2 Support Vector Regression (SVR)

SVR is suitable for small-to-medium nonlinear datasets. An RBF kernel is recommended because acoustic response can depend nonlinearly on density, thickness and frequency. Hyperparameters C, γ and ε should be tuned only within the training folds to prevent information leakage.

### 6.3 Random Forest (RF)

RF constructs an ensemble of randomized decision trees and averages their predictions. It can model nonlinearities and interactions without requiring a predefined functional form. It also provides permutation-based variable importance. RF has already been used as a feature-importance and prediction tool in recent acoustic-material ML research.

### 6.4 Extra Trees

Extremely Randomized Trees introduce additional randomization into tree construction. They are useful for capturing complex nonlinear relationships and can be benchmarked against RF using identical cross-validation splits.

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### 6.5 Gradient Boosting

Gradient Boosting sequentially adds weak learners to reduce residual error. It can provide strong predictive accuracy for structured engineering datasets, but its hyperparameters must be carefully regularized because small experimental datasets are prone to overfitting.

### 6.6 Explainable AI

SHAP values or permutation importance should be used after model development to explain which variables drive acoustic performance. Partial-dependence or accumulated-local-effect plots can then reveal how thickness, density, binder and material fraction affect predicted acoustic response. This is more informative for engineering design than reporting $R^2$ alone.

### 6.7 Optimization

After model validation, Bayesian optimization or an evolutionary algorithm such as NSGA-II can search the design space for formulations that maximize acoustic absorption while minimizing material cost, density and binder use. Candidate optimum formulations must subsequently be fabricated and experimentally verified.

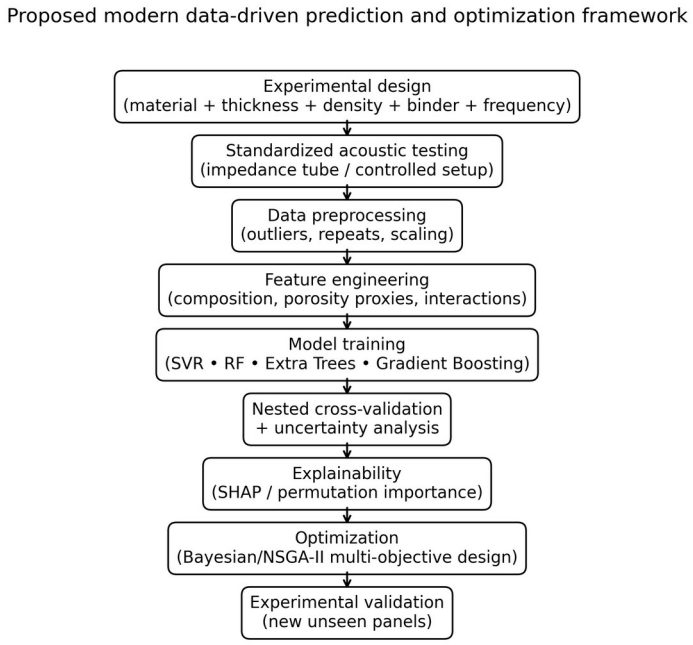



**Figure 3. Proposed modern data-driven prediction and optimization framework.**

## VII. MODEL VALIDATION PROTOCOL

The most important methodological requirement is preventing overfitting. With the present three observations, meaningful train/test ML validation is impossible. Therefore, the following protocol is recommended once the experimental dataset is expanded:

- Reserve an independent test set before model tuning; do not use it for feature selection or hyperparameter optimization.
- Use repeated k-fold cross-validation on the training data, with k selected according to the final sample size.
- Scale predictors for SVR inside each training fold only; tree models do not require scaling.
- Use nested cross-validation for hyperparameter tuning when the dataset remains relatively small.
- Report $R^2$, RMSE, MAE and, where appropriate, MAPE with caution near zero targets.
- Report prediction intervals or bootstrap uncertainty rather than only point predictions.
- Compare ML models against the quadratic response-surface baseline.
- Use parity plots, residual plots and error-versus-frequency plots.
- Validate the final optimum with new experimental specimens not used in model fitting.

**Table 4: Model evaluation metrics**

| Metric | Expression / interpretation |
|---|---|
| $R^2$ | 1 − SSE/SST; goodness of fit, but not sufficient alone |
| RMSE | sqrt(mean squared error); penalizes larger errors |
| MAE | mean absolute error; directly interpretable average error |
| MAPE | mean absolute percentage error; use cautiously for near-zero responses |
| Residual analysis | Checks systematic bias, heteroscedasticity and model inadequacy |

## VIII. PROPOSED DATABASE ARCHITECTURE

For a robust future dataset, each row should correspond to one measured frequency point for one specimen. The database should retain raw observations rather than only averaged summary values.

**Table 5: Proposed database fields**

| Field | Example / requirement |
|---|---|
| Specimen ID | Unique identifier |
| Material type | Coconut / bagasse / hybrid |
| Coconut fraction | Measured wt.% |
| Bagasse fraction | Measured wt.% |
| Binder fraction | Measured wt.% |
| Thickness | Measured mm |
| Bulk density | Measured kg/m³ |
| Frequency | Measured Hz |
| SPL without panel | Measured dB, if using the project setup |
| SPL with panel | Measured dB |
| Sound absorption coefficient | Measured α, preferred target |
| Replicate number | At least 1–3 |
| Temperature/RH | Recorded test conditions |

## IX. DISCUSSION AND ENGINEERING SIGNIFICANCE

The present evidence demonstrates that agricultural waste can be transformed into a functional noise-control panel and that the combined coconut-fibre/bagasse configuration outperformed the two individual materials in the reported setup. This result is particularly relevant because hybridization can provide a practical route for tailoring pore structure, fibre morphology and density. However, the mechanism must be verified experimentally rather than inferred from three aggregate readings.

The literature indicates that acoustic response is sensitive to density, thickness, morphology and frequency. Bagasse fibres have been reported as viable sound-absorbing materials, while coconut-fibre-containing panels have also shown useful acoustic performance. Recent work has further demonstrated the feasibility of ML prediction for acoustic materials when datasets contain sufficient structural and frequency-resolved information. Thus, the proposed workflow is aligned with current research practice, but its numerical model performance must come from newly generated experimental data rather than synthetic interpolation of the three existing observations.

From a sustainability perspective, the approach links agricultural-waste valorization with noise mitigation. The source project reports an approximate project expenditure of Rs. 2000; this should be treated as a project-scale expenditure and not as a commercial manufacturing cost. A future techno-economic assessment should include binder, processing energy, labour, moulding, drying, transport and end-of-life factors.

## X. CONCLUSIONS

Based strictly on the supplied experimental evidence, the combined coconut-fibre/bagasse panel produced the highest observed sound-level reduction, decreasing the reported level from

84 dB to 66 dB, compared with 70 dB for coconut fibre and 73 dB for bagasse. The corresponding observed reductions were 18, 14 and 11 dB. The combined panel therefore provides the strongest experimental baseline among the three tested configurations.

The study also establishes that a modern ML extension is technically promising but cannot be statistically validated using only the three available observations. The recommended next stage is a controlled, frequency-resolved dataset containing composition, thickness, density and binder variables. SVR, RF, Extra Trees and Gradient Boosting should then be benchmarked against quadratic response-surface modelling using nested cross-validation, uncertainty analysis and independent experimental validation. SHAP-based interpretation and multi-objective optimization can transform the work from a simple material comparison into a data-driven sustainable acoustic-material design framework.

## XI. ACKNOWLEDGMENT

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