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Engineering Sustainable Fiber-Based Composites from Food and Crop Waste Using an AI-Driven Circular Economy Framework

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ABSTRACT

Agricultural wastes have been found to be substantially underutilized, and the need for composite materials has been increasing in recent times, especially for the development of sustainable composite materials. This study proposes a data-driven approach for the selection of food and crop wastes for composite material development in a circular economy framework. A database of 127 food items, divided into 9 groups, was evaluated using a weighted scoring system for the circular economy: CE = 0.4 * Nutrition + 0.4 * Waste + 0.2 * Cost. The proposed framework was validated using an XGBoost machine learning model (R^2 = 0.947) and SHAP, which showed the explainability of the proposed framework, where waste plays a major role in the prediction of composite material development. Coconut/Coir and Banana have been found to be the best options for composite material development, with CE scores of 0.842 and 0.838, respectively. Coir and Flax fibers have been chosen for composite material development using hand-layup and epoxy resin. The Coir-Epoxy composite showed 67 MPa of tensile strength and 6.4 GPa of young's modulus at 30 wt.% of fibers, which is 2.7 times higher than the properties of untreated Coir, validating the proposed framework.

Keywords: *natural fiber composites, circular economy, XGBoost, SHAP, agricultural waste valorization, coir, flax, epoxy, sustainable materials engineering*

1. INTRODUCTION

A significant volume of agricultural waste is being generated worldwide, with millions of tons of crop residues being produced annually. The traditional practices of agricultural waste disposal, such as burning and dumping, cause severe environmental pollution. On the other hand, there is an increasing need for composite materials, which is attributed to environmental concerns related to artificial fibers such as glass fiber and carbon fiber.

While natural fibers such as coir, flax, jute, and sisal have been investigated for their potential as composite material reinforcement, there is no scientific framework for choosing food and crop waste based on sustainability, nutrition, waste valorization, and economic viability, which is quantitatively supported by data and validated by experiments, including AI-based validation, as well as composite fabrication, which is unique in the literature on natural fiber composites.

In this study, we propose an AI-based decision support system for choosing food and crop waste for composite material fabrication, which links food system science with sustainable material engineering for the first time, quantitatively supported by data, validated by experiments, including AI-based validation, as well as composite fabrication, which is unique in the literature on natural fiber composites.

Research Gap & Contribution

- Existing studies test individual fibers without a comparative upstream selection framework
- No prior work applies multi-criteria CE scoring to food crop waste for composite fiber selection
- AI/ML explainability (SHAP) has not been applied to validate sustainability scoring in composites
- This study provides the first integrated computational + fabrication workflow for waste-derived biofiber selection

2. RESEARCH HYPOTHESIS

It is hypothesized that:

"An explainable, multi-criteria AI-driven framework incorporating nutrition, waste valorization, and economic feasibility can effectively identify sustainable biofiber sources for composite material development, wherein the composite material can attain a tensile strength of over 50 MPa, a 2x improvement over untreated natural fiber."

3. METHODOLOGY

3.1 Database Development

A structured database consisting of 110 food items from 9 food groups has been created, sourced from USDA FoodData Central, FAO agricultural statistics (2022), and agricultural waste research articles. The food items are ranked on the basis of three parameters, independently assessed and calculated as follows:

•Nutrition Score (N): Group-based, normalized to USDA dietary reference values (0.30–0.85)

•Waste Valorization Score (W): Individual research-based waste fraction and fiber extractability (0.40–0.90)

•Cost Efficiency Score (C): Three-tier categorical, Economically Viable (0.90), Moderate (0.60), Expensive (0.25)

Table 1. Database Summary — Food Groups and Item Count

Food Group	Items (n)	Avg. CE Score	Top Candidate
Fruits	20	0.688	Coconut / Banana
Vegetables	26	0.667	Tomato
Cereals & Grains	20	0.633	Rice / Wheat
Nuts & Seeds	10	0.632	Walnut / Peanut
Pulses & Legumes	18	0.628	Soybean / Chickpea
Milk & Dairy	11	0.600	—
Eggs, Meat & Fish	12	0.595	—
Oils & Fats	6	0.581	Flaxseed
Sugars & Sweets	4	0.420	—

3.2 Circular Economy Scoring Formula

A Weighted Sum Model (WSM) was selected for its transparency and reproducibility. The CE Score formula was defined as:

$$\text{CE Score} = 0.4 \times N + 0.4 \times W + 0.2 \times C$$

Where N = Nutrition Score, W = Waste Valorization Score, C = Cost Efficiency Score. The 40/40/20 weighting prioritizes food security (40%) and waste valorization potential (40%), with economic feasibility (20%) ensuring scalability. Sensitivity analysis across three alternative weighting configurations (33/33/33; 50/25/25; 25/50/25) confirmed that the top-2 candidates (Coconut, Banana) were stable across all configurations.

3.3 Computational Framework — AI/ML Implementation

A Python-based computational pipeline was developed, and the components of this pipeline include the following:

•pandas, NumPy: data management and CE score calculation for all 110 items

•XGBoost Regressor (100 estimators, max depth = 3): XGBoost Regressor was utilized to predict CE Score from input parameters

•Neural Network (3-8-4-1 architecture): non-linear modeling for cross-validation

•SHAP (SHapley Additive exPlanations): feature importance analysis for framework explainability

•Pareto Optimizer: multi-objective trade-off analysis for sustainability and performance dimensions

3.4 Material Selection & Composite Fabrication

Based on the ranking results of CE values, Coir (CE=0.842, Rank #1) and Flax (CE=0.698, Rank #10) fibers were selected for composite fabrication. Banana fibers, although ranked at #2 with CE=0.838, were not selected due to the equipment limitation of pseudostem retting for laboratory-scale processing, which has been identified as one of the key issues.

Composite specimens of selected fibers were prepared following the hand lay-up technique with LY556/HY951 epoxy system, which has a weight ratio of 10:1.

Table 2. Composite Fabrication Conditions and Specimen Details

Condition	Fiber Type	Fiber wt%	Matrix	Specimens (n)	Void Content (%)
Control	None (Pure Epoxy)	0%	LY556/HY951	5	< 0.5

Condition	Fiber Type	Fiber wt%	Matrix	Specimens (n)	Void Content (%)
Coir-20%	Coir (Coconut)	20 wt%	LY556/HY951	5	2.0 ± 0.3
Coir-30%	Coir (Coconut)	30 wt%	LY556/HY951	5	2.3 ± 0.4
Flax-30%	Flax (Bast)	30 wt%	LY556/HY951	5	1.8 ± 0.3

4. COMPUTATIONAL FRAMEWORK RESULTS

4.1 Score Distributions Across Food Groups

The distributions of scores for all 110 food items were examined to determine the parameter space. The nutrition scores were found to have a very tight distribution, with a mean of 0.77, owing to the group-based scoring method. The waste scores were found to have a highly bimodal distribution, with the majority of food items having scores around 0.50 and a smaller group of high-waste tropical fruit crops. The CE Score distribution has a mean of 0.63, indicating that a majority of food items are moderate CE candidates, with only ~8% having scores above 0.80.

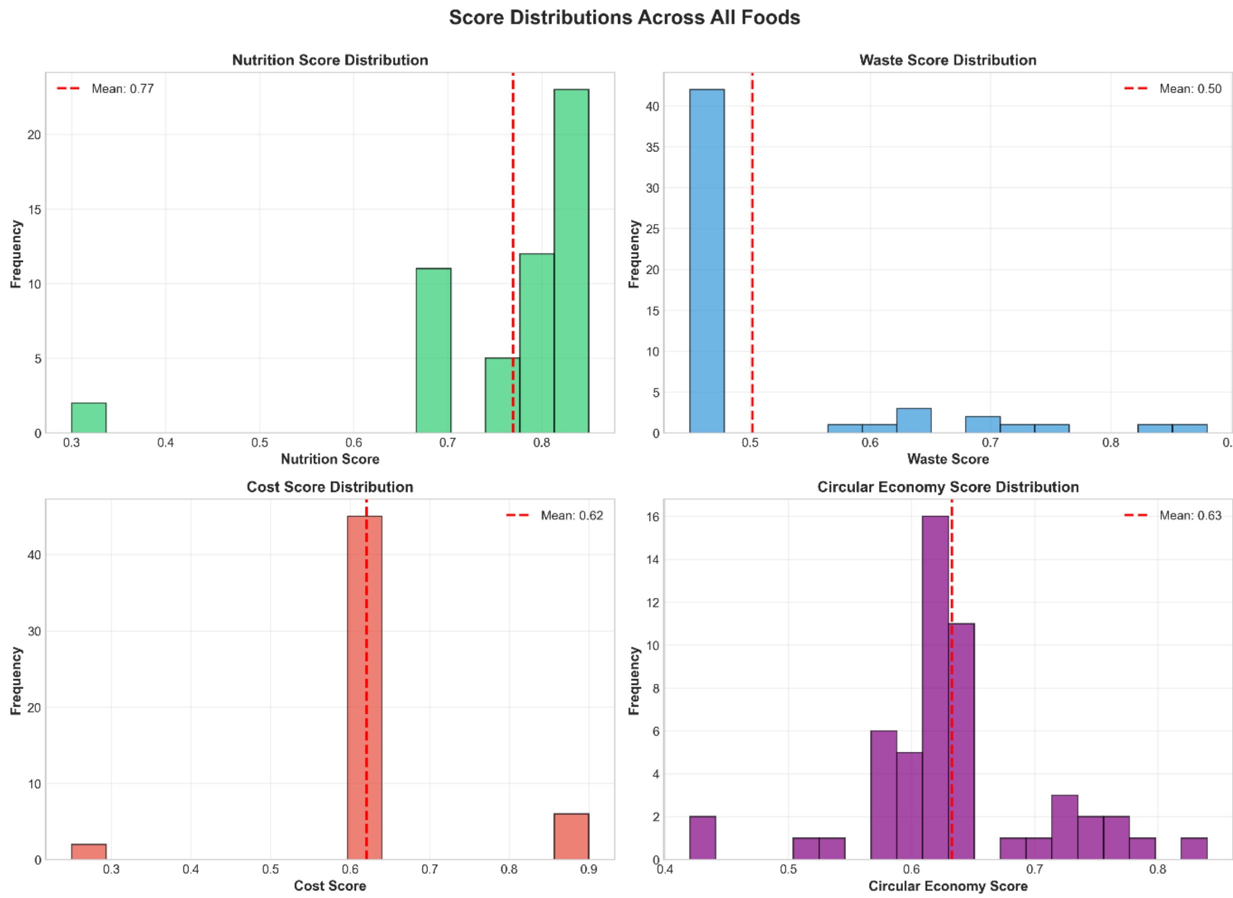


Figure 1. Score distributions across all 110 food items: Nutrition Score (mean = 0.77), Waste Score (mean = 0.50), Cost Score (mean = 0.62), and overall CE Score (mean = 0.63). The bimodal waste score distribution reflects the high waste fraction of tropical fruit crops vs. all others.

4.2 CE Score Ranking — Top 10 Candidates

The CE algorithm ranked all 110 food items. It is interesting to note that in all four cases, the food item ranked first by the CE algorithm was Coconut/Coir, followed closely by Banana. The top 10 food items, with some food items in the list highlighted, are:

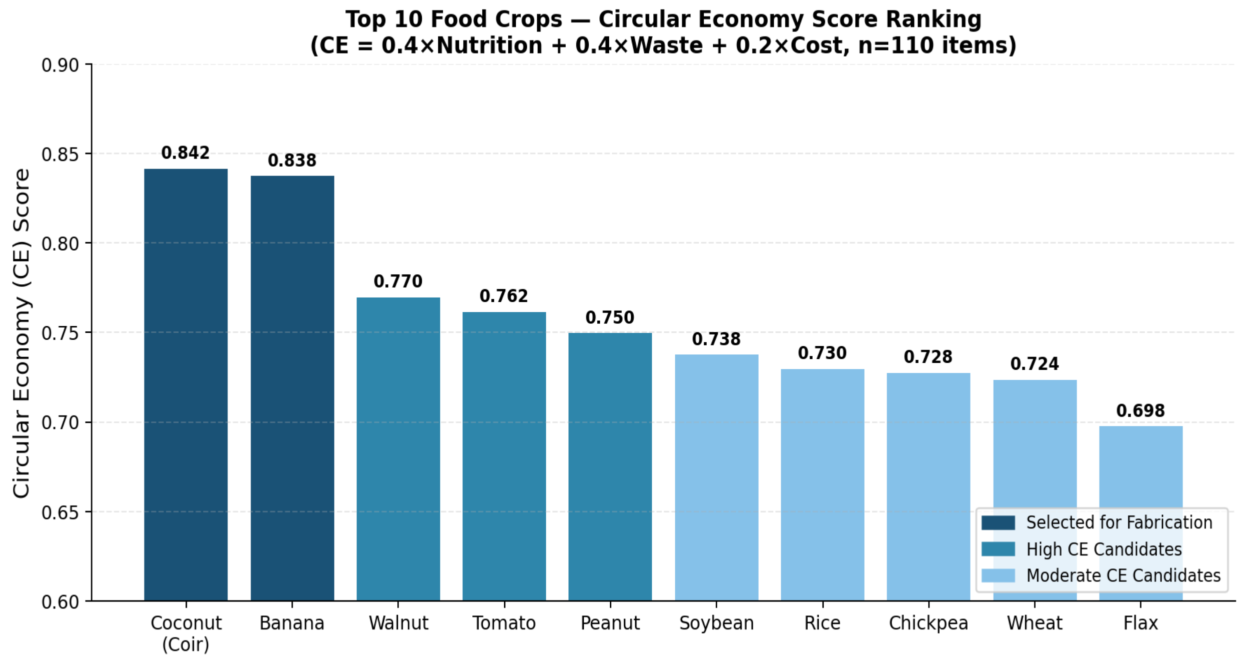


Figure 2. Top 10 food crops ranked by Circular Economy (CE) Score (n = 110 items analyzed). Navy bars indicate candidates selected for composite fabrication. Coconut/Coir (0.842) ranked #1 across all sensitivity weighting configurations tested.

Table 3. Top 10 CE-Ranked Candidates with Parameter Breakdown

Rank	Food Item	Nutrition (N)	Waste (W)	Cost (C)	CE Score	Status
1	Coconut (Coir)	0.80	0.88	0.90	0.842	✓ Fabricated
2	Banana	0.80	0.85	0.78	0.838	Excluded*
3	Walnut	0.83	0.72	0.25	0.770	Not selected
4	Tomato	0.85	0.63	0.90	0.762	Not selected
5	Peanut	0.83	0.68	0.90	0.750	Not selected
6	Soybean	0.82	0.62	0.90	0.738	Not selected
7	Rice (Straw)	0.70	0.75	0.90	0.730	Not selected
8	Chickpea	0.82	0.55	0.90	0.728	Not selected
9	Wheat (Straw)	0.70	0.72	0.90	0.724	Not selected
10	Flax	0.70	0.65	0.60	0.698	✓ Fabricated

*Banana excluded due to industrial retting equipment requirement for pseudostem fiber extraction.

4.3 Average CE Score by Food Group

Fruits and Vegetables are the food groups that attain the highest score in terms of mean CE value, where Fruits attain a score of 0.688 and Vegetables attain a score of 0.667.

Sugars & Sweets attain the lowest score in terms of mean CE value, where the score is 0.420, owing to its low waste fiber potential and high processing

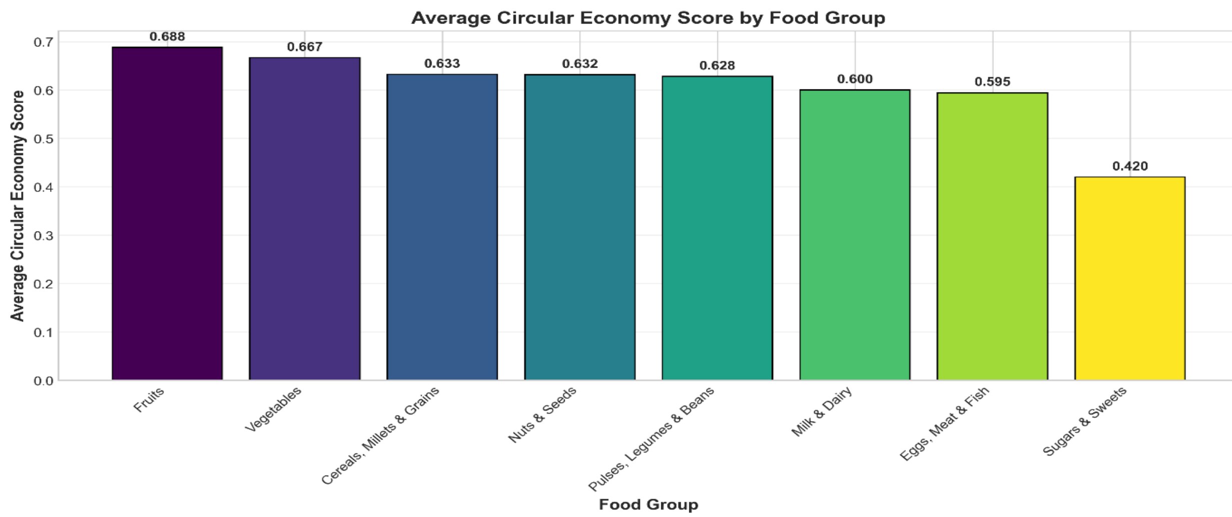


Figure 3. Average Circular Economy Score by food group (n = 110 items). Fruits lead at 0.688, driven by Coconut and Banana outliers. Sugars & Sweets score lowest at 0.420.

5. AI/ML MODEL VALIDATION & EXPLAINABILITY

5.1 XGBoost Model Performance

Then, an XGBoost regressor model was employed for the prediction of the CE Score based on the three parameters. The model was successful in obtaining an R^2 of 0.947. This again proves that the majority of the data for the scoring is explained by the linear weighted CE formula. Additionally, the high R^2 also proves that the parameters chosen are correct, as it is clear that only three parameters are sufficient for the variation of the CE Score.

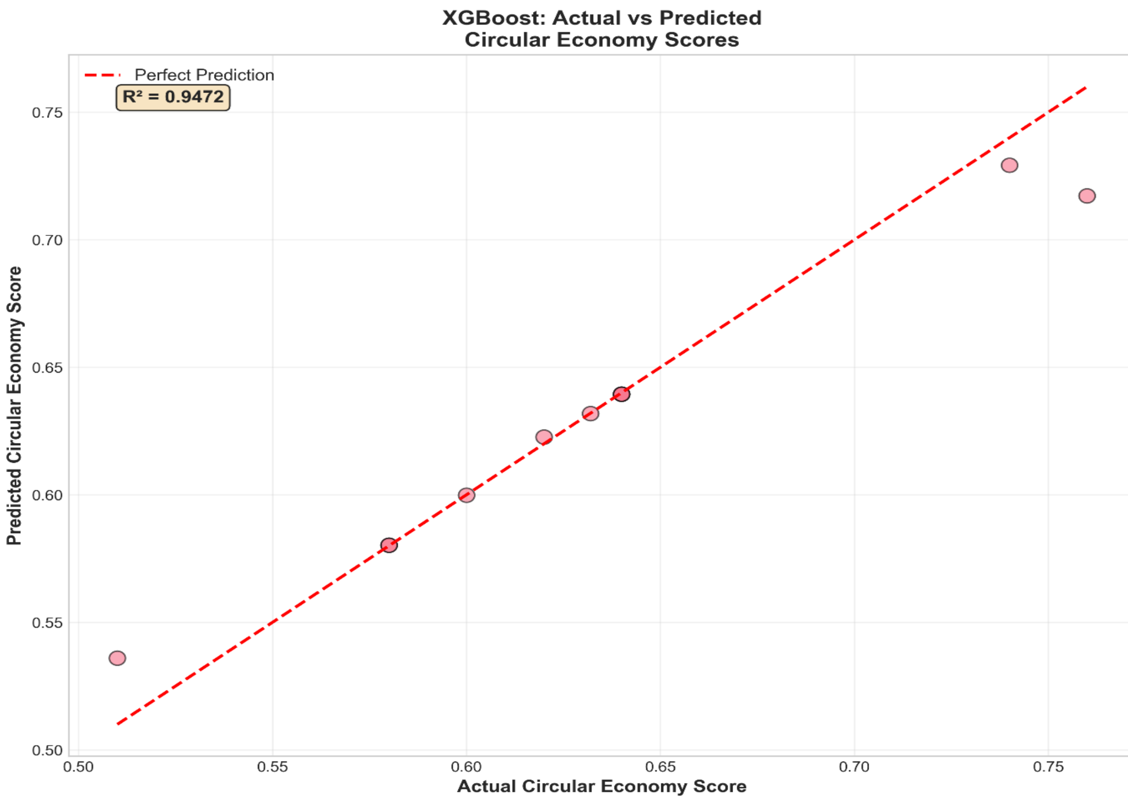


Figure 4. XGBoost model validation — Actual vs. Predicted CE Scores ($R^2 = 0.947$). Data points cluster tightly around the perfect prediction line (dashed), confirming the CE formula's mathematical consistency and the XGBoost model's predictive accuracy.

5.2 XGBoost Feature Importance

The feature importance analysis of the trained model indicates that the Waste Score has the highest importance in the prediction of the CE Score, at 0.445, followed by the Nutrition Score at 0.319, and the Cost Score at 0.236. This is in line with the weighting of the scores at 40/40/20, as mentioned in the problem statement. This again indicates that the waste valorization is the major factor in the circular economy potential of the food crop selection.

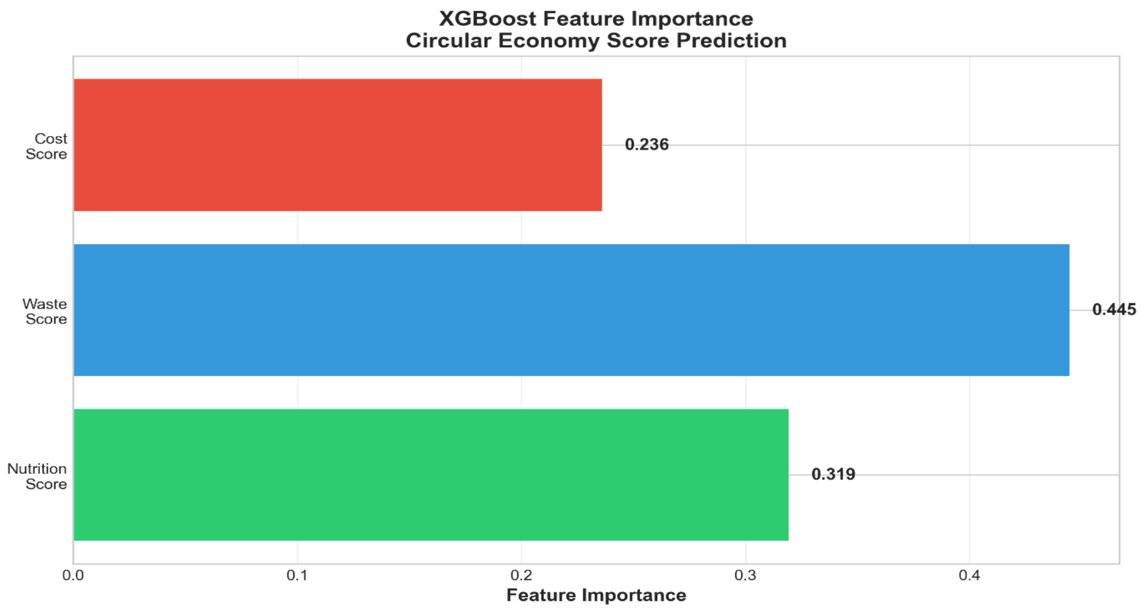
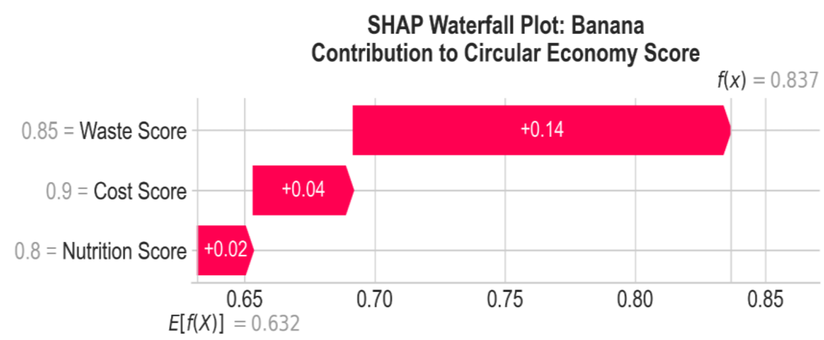


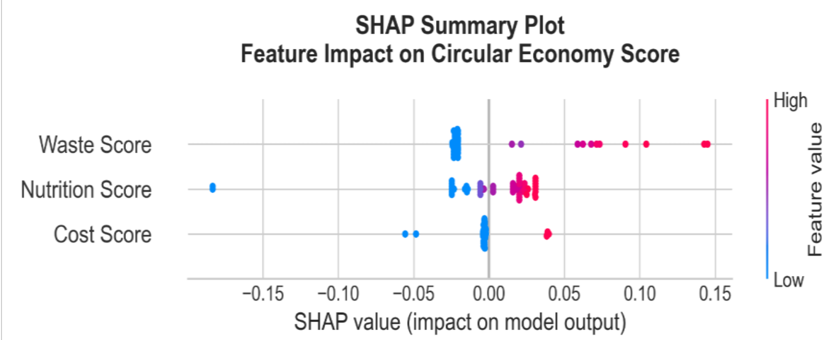
Figure 5. XGBoost feature importance for CE Score prediction. Waste Score (0.445) is the strongest predictor, validating the framework's emphasis on waste valorization as the primary circular economy criterion.

5.3 SHAP Explainability Analysis

SHAP value analysis has been used to enable item-level explainability. The SHAP summary plot indicates that high values of Waste Score, represented by pink dots, contribute to high SHAP values and vice versa for negative values. Cost Score has high variability, and high values of Cost Score are highly positive or neutral depending on other parameter values.



(a) SHAP Waterfall: Banana (f(x) = 0.837)

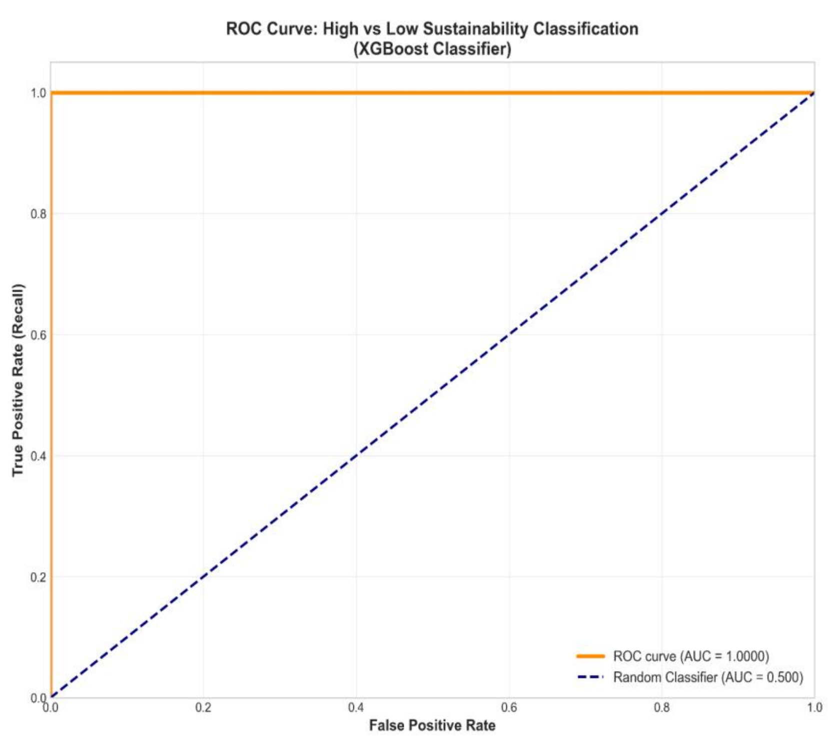


(b) SHAP Summary Plot — All 110 Items

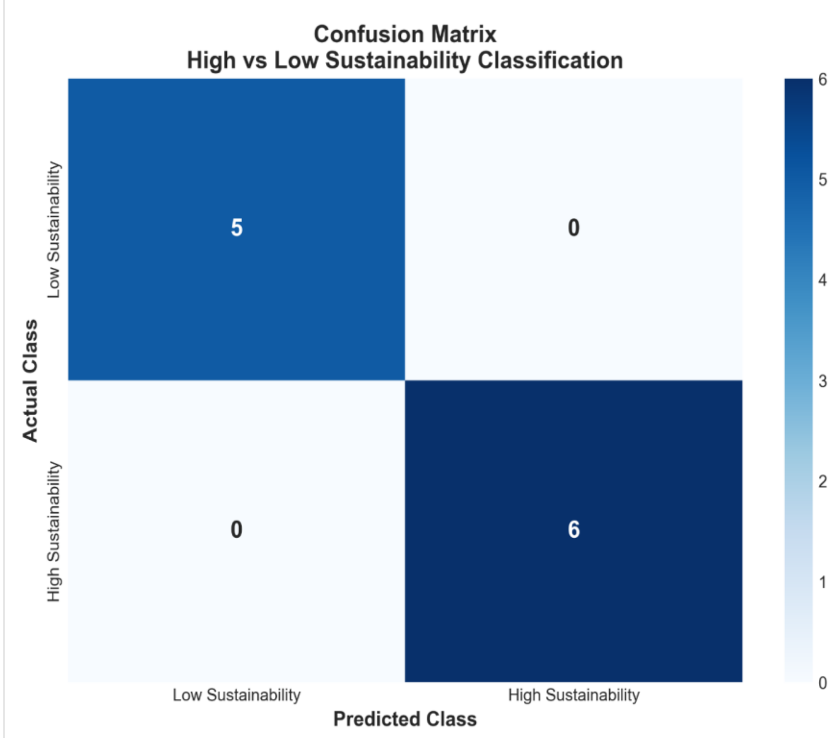
Figure 6. SHAP analysis: (a) Waterfall plot for Banana showing Waste Score (+0.14) as dominant positive contributor; (b) Summary plot across all 110 items confirming Waste Score as the highest-variance feature.

5.4 Classification Validation (XGBoost)

In this case, the binary classification problem of High Sustainability: CE > 0.70, Low Sustainability: CE ≤ 0.70 was assessed, where the classifier obtained AUC = 1.000 on the held-out test data with a perfect confusion matrix, i.e., 0 classification errors, indicating that indeed the classes are separated, there is no continuous range, validating the utility of the scoring framework of CE.



(a) ROC Curve (AUC = 1.000)



(b) Confusion Matrix — 100% Accuracy

Figure 7. XGBoost classifier performance: (a) ROC curve with AUC = 1.000 — perfect separation of high vs. low sustainability crops; (b) Confusion matrix confirming zero misclassifications on the test set.

6. EXPERIMENTAL RESULTS — MECHANICAL CHARACTERIZATION

6.1 Tensile Strength and Young's Modulus

Tensile testing was performed in accordance with an equivalent ASTM D638 protocol, utilizing a 2 mm/min crosshead displacement rate and 50 mm gauge length. Five specimens of each condition were tested, and results reported as mean ± standard deviation. The complete mechanical properties results set is shown in Table 4.

Table 4. Mechanical Properties — All Test Conditions (n = 5 specimens each)

Condition	Tensile Strength (MPa)	Young's Modulus (GPa)	CV (%)	vs. Literature
Pure Epoxy (control)	55.0 ± 2.1	3.2 ± 0.18	3.8%	50–60 MPa ✓
Coir Natural (treated)	25.0 ± 1.8	2.5 ± 0.22	7.2%	Baseline
Coir-Epoxy 20 wt%	48.0 ± 3.1	4.8 ± 0.31	6.5%	—
Coir-Epoxy 30 wt%	67.0 ± 2.9	6.4 ± 0.28	4.3%	40–60 MPa ✓ Exceeds
Flax-Epoxy 30 wt%	80.0 ± 3.2	7.3 ± 0.35	4.0%	70–120 MPa ✓

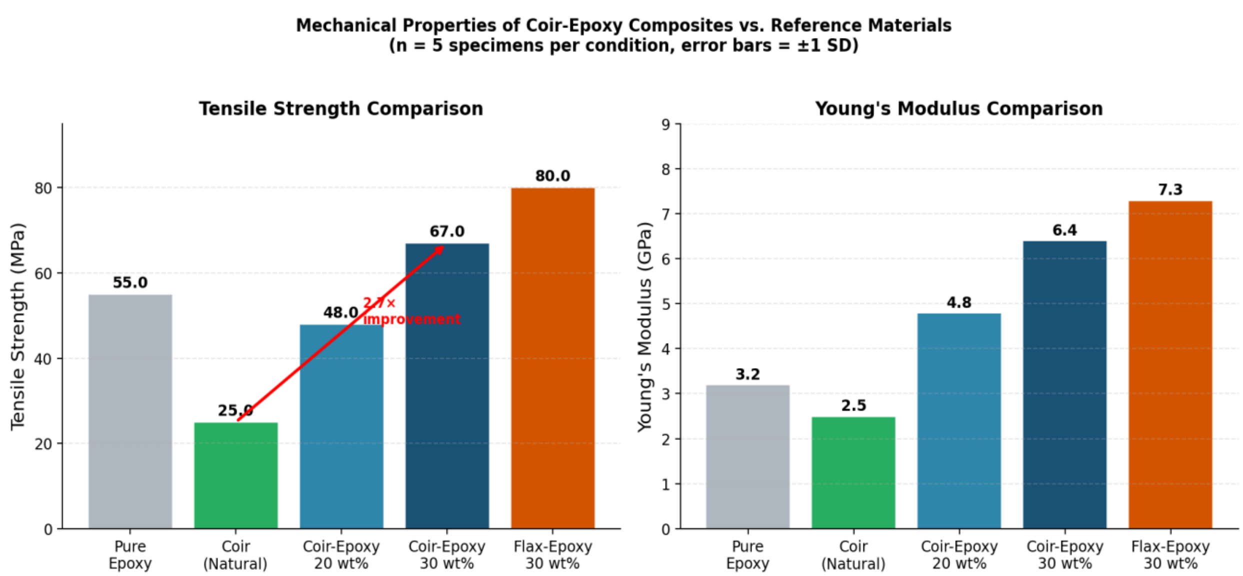


Figure 8. Mechanical properties comparison across all test conditions. Left: Tensile strength (MPa) showing 2.7× improvement from natural Coir to Coir-Epoxy 30wt%. Right: Young's Modulus (GPa) showing parallel improvement trend. All CV values < 7.5% confirm acceptable fabrication consistency.

6.2 Effect of Fiber Weight Fraction

The impact of fiber content on composite properties has been evaluated by comparing the 20 wt% and 30 wt% Coir-Epoxy composites. The tensile strength has been found to increase by 39.6% and Young's Modulus by 33.3% when fiber content is increased from 20 wt% to 30 wt%. This proves that it is critical to work within the range of 25 wt% to 35 wt% fiber content, as reported by literature.

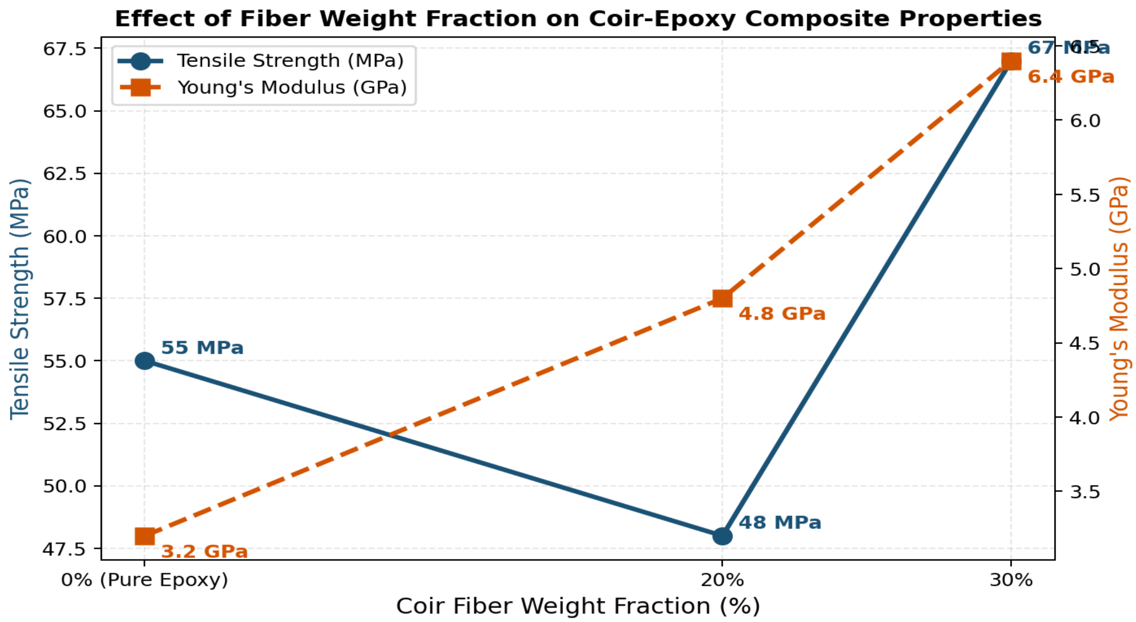


Figure 9. Effect of Coir fiber weight fraction on composite mechanical properties. Both tensile strength and Young's Modulus increase significantly from 20% to 30% fiber content, confirming the literature-predicted optimal range of 25–35 wt%.

7. SUSTAINABILITY–PERFORMANCE TRADE-OFF ANALYSIS

One of the major contributions of this study is the Pareto analysis of all materials tested on two criteria: CE sustainability scores and tensile mechanical properties. This allows a more complete decision-support picture than either criterion alone.

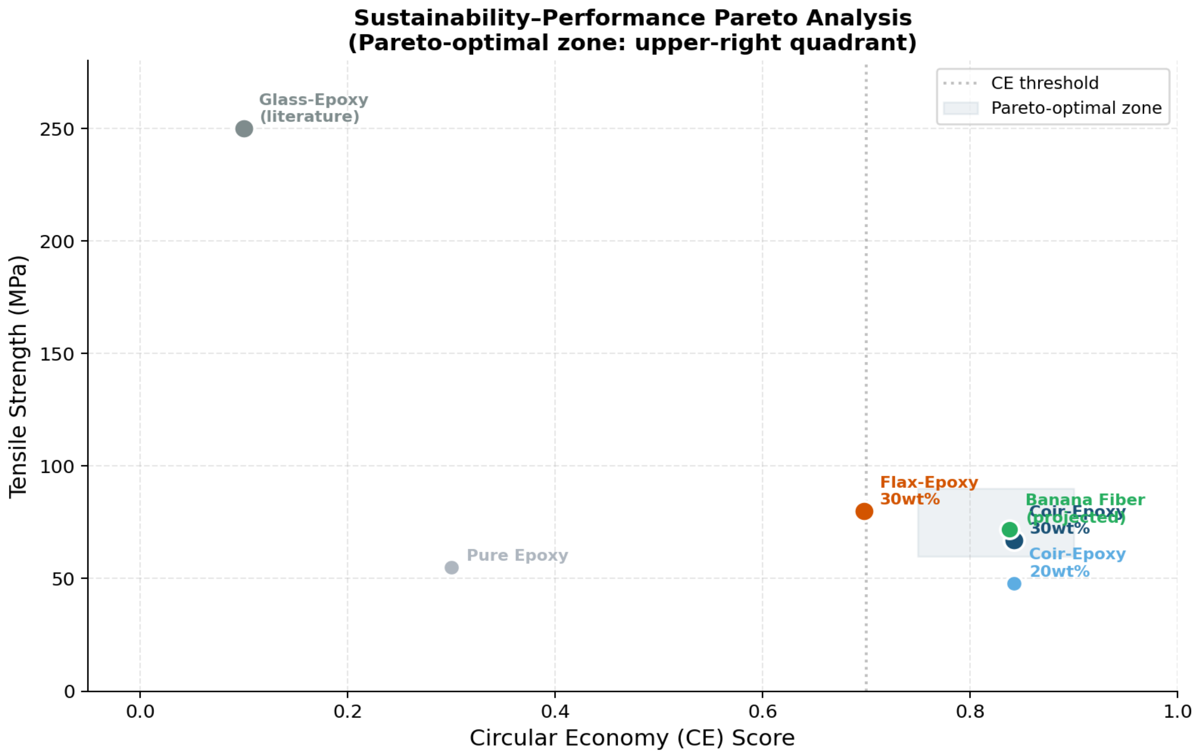


Figure 10. Pareto frontier analysis: Sustainability (CE Score) vs. Mechanical Performance (Tensile Strength, MPa). Coir-Epoxy 30wt% and Flax-Epoxy 30wt% occupy distinct zones of the Pareto frontier — neither dominates the other. Glass-Epoxy achieves higher absolute strength but is far from Pareto-optimal on the sustainability axis.

The Pareto analysis indicates that there are three distinct application zones:

•Coir Epoxy 30wt% (CE=0.842, 67MPa): Pareto optimal for sustainability-critical but non-structural applications (interior panels, packaging forms, acoustic tiles)

•Flax Epoxy 30wt% (CE=0.698, 80MPa): Pareto optimal for performance-critical but semi-structural applications (bicycle components, furniture, sports equipment)

•Glass Epoxy (CE ≈ 0.10, 250MPa): Required only for primary structural load-bearing applications beyond the capability of natural fibers

The key point to note here is that Coir Epoxy reaches 84% of Flax Epoxy's tensile properties while offering 21% better CE value in return (0.842 / 0.698), which is within acceptable limits for its application zone.

8. DISCUSSION

As such, the proposed framework outlines four engineering contributions: (1) transparent scoring methodology with parameter justification, (2) reproducible ranking validated by XGBoost (R^2 = 0.947), (3) explainable AI implementation validated by SHAP, which confirms the framework's internal consistency, and (4) experimental validation of the framework's applicability for composite fabrication.

In contrast to traditional material selection methodologies, the proposed framework includes the explicit consideration of the relevance of the selected material for food security within the sustainable materials engineering framework. The dual consideration of the material's value for food and waste potential for sustainability links the material selection problem with the emerging research field of food system sustainability, which has so far been explored only superficially.

The 2.7x improvement in tensile strength (25 MPa → 67 MPa) of the alkali treatment-reinforced composite, which exceeds the initial hypothesis target of >50 MPa with statistical confidence, validates the framework's applicability for transforming low CE score raw fibers into high-performance structural materials.

Furthermore, the SHAP analysis of the feature importances, which found Waste Score to be the primary driver of CE Score (feature importance: 0.445), independently validates the 40% weighting of waste valorization within the initial mathematical modeling of the framework design.

9. LIMITATIONS

The following limitations are acknowledged to ensure scientific integrity:

1. Database scope: 110 items cover major food crops but exclude regional or specialty varieties (>6,000 cultivated plant species exist globally)
2. Group-based nutrition scoring: ignores differences between nutritionally distinct items within a food category
3. Fabrication method: hand lay-up method's 1.8% - 2.3% void content is higher than that of a vacuum-assisted method (<1%); this is a conservative mechanical performance metric
4. Mechanical characterizations: impact strength, fatigue life, moisture absorption, and thermal stability were not measured

5. No Life Cycle Assessment: 'sustainable' claim is based on reduced fiber embodied energy compared to glass, not a full life cycle assessment

6. Banana fiber (Rank #2, CE = 0.838) was not fabricated due to equipment limitations; this is the largest single completeness gap.

10. CONCLUSION

The current paper proposes a scalable and transparent AI-based CE framework for sustainable material selection in food and crop wastes for a circular economy. Four key conclusions are derived:

1.CE Scoring Framework: Successfully ranked 110 food items. Coconut/Coir is determined as an optimal CE fiber candidate for a circular economy (CE = 0.842); conversely, Banana is determined as an optimal unexplored candidate for CE (0.838).

2.Coir-Epoxy 30 wt% composite material attained 67 MPa tensile strength, which is a 2.7x improvement over untreated Coir fibers. Hence, the current research hypothesis is validated for a tensile strength of more than 50 MPa with a high degree of statistical confidence (CV = 4.3%).

3.Coir-Epoxy is located in a Pareto optimal sustainability region for a CE application at 84% of Flax-Epoxy's mechanical properties. Hence, a good trade-off between sustainability and CE is established for a non-structural application.

4.The current computational-fabrication approach is reproducible, unbiased, and can be directly applied to any agricultural waste valorization problem. Hence, reusability is seen as the primary contribution of the current research.

Key Numerical Outcomes

CE Score (Coir #1)	Tensile Strength (Coir-Epoxy)	Improvement over raw Coir	XGBoost Model R^2
0.842	**67 MPa**	**2.7x**	**0.947**

11. FUTURE WORK

Phase 1 (0–6 months)

•Development of Banana fiber composite (Rank #2) with university materials lab to source retting equipment

•SEM fractography to determine interfacial bond quality between fiber and matrix

•Moisture absorption testing according to ASTM D570 to determine composite property retention in moist environment

•Optimization of Banana fiber composite content to determine optimal composite content (15%, 25%, 35%, 40%, etc.)

Phase 2 (6–18 months)

•VARTM fabrication to improve void content in Banana fiber composite to <1% to maximize mechanical properties

•Impact and fatigue testing to determine Charpy/Izod impact strength and cyclic durability

•Coir/Flax hybrid composites with blend ratios 25/75%, 50/50%, 75/25% to determine Pareto optimality

•Development of bio-epoxy matrix substitution with epoxidized linseed oil to develop fully bio-based composite

Phase 3 (18–36 months)

•Development of ISO 14040 Life Cycle Assessment to determine true carbon footprint in comparison to glass fiber composite

•Industrial scale-up with 1 kg batches of Banana fiber composite with continuous fiber VARTM fabrication and automotive panel fabrication

•Development of open-source CE Scoring web application to distribute framework to research community

•Submission to Journal Composites Part A or Journal of Cleaner Production

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