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Machine Learning-Driven Evaluation of Sustainability Performance of Building Materials in Kenya

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Abstract: **Sustainability in Kenya's construction sector faces critical challenges due to fragmented data systems, weak regulatory enforcement, and limited analytical frameworks for evaluating building material performance. Although sustainable construction has gained prominence, decision-making remains largely subjective and policy-driven rather than performance-evaluated. This study addresses the problem by developing a machine learning–driven framework to quantitatively assess the Sustainability Performance Index (SPI) of building materials in Kenya. Using survey data from 328 construction professionals and twenty normalized indicators spanning economic, environmental, social, and institutional dimensions, an Artificial Neural Network (ANN) model was trained and validated through 10-fold cross-validation. The ANN captured nonlinear dependencies among the SEET (Social, Environmental, Economic, Technological) parameters, achieving a predictive accuracy of $R^2 = 0.89$ and RMSE ≈ 0.13. Shapley Additive Explanations (SHAP) and Permutation Feature Importance analyses revealed Durability, Energy Efficiency, and Waste Reduction as dominant predictors, with Policy Enforcement and Awareness Level as critical institutional amplifiers. The findings demonstrate that the proposed ANN framework effectively operationalizes sustainability evaluation, providing policymakers and practitioners with an interpretable, evidence-based tool for material selection and performance benchmarking. The study concludes that integrating machine learning into sustainability assessment enhances transparency and adaptive governance in Kenya's built environment. It recommends embedding such data-driven SPI models into national building codes, procurement systems, and housing policy audits to align construction practices with the Sustainable Development Goals (SDGs 9, 11, and 12). Future research should expand empirical datasets, integrate lifecycle costing, and hybridize neural networks with fuzzy or ensemble models to improve generalization across regional contexts.**

Keywords: **Artificial Neural Network, Building Materials, Machine Learning, Sustainability, Sustainability Performance Index.**

I. INTRODUCTION

A. Background Information

Sustainability in the built environment has become central to addressing climate change, resource depletion, and socio-economic inequality [1]. Globally, the construction sector is one of the most resource-intensive and environmentally impactful industries [2], accounting for approximately 39% of global CO_2 emissions and 40% of raw material consumption (UNEP, 2023) [3]. It consumes more than 40% of total energy and contributes an equivalent share of greenhouse gas (GHG) emissions [4]. Despite the proliferation of international sustainability assessment frameworks such as LEED, BREEAM, and SBTool, these tools inadequately capture the realities of developing economies, where climatic, economic, and institutional contexts differ significantly from those of the Global North.

In Kenya, the construction sector plays a pivotal role in economic growth [5], yet it faces mounting challenges linked to environmental degradation, material inefficiency, and waste generation. The country's rapid urbanization, estimated at 4.1% annually and projected to push the urban population beyond 60% by 2050 [6], has intensified the demand for affordable housing and building materials. The State Department for Housing and Urban Development reported that Kenya's population grew by 2.7% per year between 2011 and 2015, reaching approximately 52 million by 2020, leading to unprecedented pressure on finite natural resources such as sand, limestone, and timber [7]. Consequently, the sector now stands at the intersection of economic development and environmental degradation, demanding urgent integration of data-driven sustainability evaluation systems.

Despite increased attention to green building technologies, the Kenyan construction industry continues to suffer from fragmented data systems, weak enforcement of sustainability regulations, and limited analytical frameworks for evaluating material performance. Herda *et al.* [7] found that less than 20% of Kenya-specific material performance data is currently available, with nearly half of the required datasets missing. This data gap undermines the credibility of sustainability claims, complicates policy formulation, and discourages private-sector innovation. The absence of comprehensive databases and standardized performance metrics has made decision-making in material selection largely subjective, guided more by initial cost than by empirical sustainability indicators. This limitation is particularly critical as the government promotes Appropriate Building Materials and Technologies (ABMTs) under its affordable housing initiatives, yet lacks robust evidence to compare environmental, economic, and social performance outcomes.

Recent empirical studies reveal that while awareness of sustainable construction is rising, its implementation remains inconsistent and policy-driven rather than performance-evaluated. Odongo, Lamka, and King'oriah [8] reported that among 439 surveyed professionals in Kenya, the mean sustainability impact perception score was 3.94 out of 5, reflecting optimism but also uneven adoption across economic, environmental, and social dimensions. Another study by Odongo *et al.* [4] identified critical inhibitors such as first-cost premiums, insufficient technical expertise, limited access to sustainability data, and weak enforcement of building codes. These findings underscore that Kenya's transition toward a low-carbon built environment is less constrained by policy intent than by limited analytical capacity for evidence-based evaluation.

Globally, data analytics and artificial intelligence (AI) are increasingly transforming sustainability assessment by enabling predictive and adaptive modeling. Machine learning (ML) techniques—especially Artificial Neural Networks (ANNs), decision trees, and support vector regression—have demonstrated superior ability to analyze high-dimensional sustainability datasets and capture complex nonlinear relationships among performance variables. Ekeh *et al.* [9] showed that ML algorithms can optimize environmental policy and identify key sustainability drivers by learning from multi-criteria datasets. Such methods outperform traditional linear regression and index-based evaluations, which fail to account for interdependencies among economic, environmental, and social indicators. Integrating ML into material evaluation therefore presents an opportunity to automate pattern detection, quantify uncertainty, and enable data-driven decision-making for sustainable construction.

Kenya's policy landscape provides a strong yet underutilized foundation for applying such analytical innovations. Sangori *et al.* [10] emphasized that the effectiveness of sustainability policies depends on harmonized regulations, consistent monitoring mechanisms, and adequate technical standards. However, implementation remains fragmented by institutional overlaps and inadequate digital infrastructure. The same challenge affects the monitoring of sustainability indicators in construction materials, where existing systems are descriptive, static, and rarely predictive. Machine learning-driven frameworks can address these deficiencies by processing multi-criteria indicators—such as energy efficiency, embodied carbon, resource conservation, durability, and social inclusivity—into quantifiable sustainability performance indices.

The legal and governance dimensions of sustainability further justify the need for computational approaches. Mauerhofer, Rupo, and Tarquinio [11] argue that modern sustainability law increasingly prioritizes measurable environmental outcomes and accountability mechanisms aligned with the United Nations' 2030 Agenda for Sustainable Development. Similarly, Kenya's Vision 2030 identifies sustainable infrastructure and green innovation as key enablers of long-term economic resilience. Yet, existing sustainability evaluation frameworks in the country remain largely qualitative and fragmented, offering limited predictive capacity for real-time policy or investment decisions. The integration of ML-based analytics can operationalize these policy goals by enabling continuous learning, scenario analysis, and benchmarking of local materials against global sustainability standards.

The implications of Kenya's limited data and analytical infrastructure extend beyond technical inefficiency to economic and environmental risks. The construction sector contributes significantly to the national GDP but also accounts for a large share of resource depletion and waste generation. Studies estimate that over 60% of urban waste in Nairobi originates from construction and demolition activities, while cement production alone is responsible for approximately 7–8% of global CO_2 emissions [12]. These trends highlight the unsustainable trajectory of current practices and the urgent need to decouple economic growth from environmental degradation. If unaddressed, these challenges could jeopardize Kenya's climate commitments under the Paris Agreement and hinder progress toward the Sustainable Development Goals (SDGs).

To address these challenges, there is a growing consensus on the need for quantitative, data-driven, and context-specific evaluation frameworks. The use of Artificial Neural Networks (ANNs) provides a powerful means of modeling nonlinear interactions among sustainability indicators and predicting performance outcomes for different material types and project contexts. Unlike static index methods, ANNs can learn from historical and real-time data, adapt to local conditions, and deliver transparent and reproducible assessments. Applying this technology in Kenya's construction sector will provide policymakers, developers, and researchers with an evidence-based tool for selecting materials that balance economic viability, environmental integrity, and social value.

In summary, Kenya's construction industry stands at a pivotal moment. Rapid urbanization and infrastructure demand offer opportunities for growth but also intensify environmental risks. The absence of reliable sustainability data and predictive evaluation methods continues to constrain informed decision-making. This proposed study—*Machine Learning-Driven Evaluation of Sustainability Performance of Building Materials in Kenya*—seeks to bridge these gaps by developing a computational framework that integrates empirical data, sustainability indicators, and artificial intelligence. Through the application of machine learning, particularly ANN-based modeling, the study aims to evaluate and predict the sustainability performance of building materials, providing a replicable, data-driven foundation for sustainable construction in Kenya's built environment.

B. Contribution

The primary contribution of this study lies in advancing a computationally grounded, interpretable, and context-sensitive approach for assessing sustainability performance of building materials in developing economies. Technically, the research introduces a bounded Artificial Neural Network (ANN) architecture that models complex, nonlinear interactions among twenty normalized SEET indicators—an analytical depth that conventional linear or additive models have failed to capture. The model's integration of SHAP and Permutation Feature Importance (PFI) provides transparency in identifying the relative influence of variables, overcoming the "black-box" limitation of neural networks.

Empirically, the study generates a data-driven Sustainability Performance Index (SPI) specific to Kenya's construction sector—the first of its kind—allowing quantitative benchmarking of materials and practices. Methodologically, the study demonstrates how Likert-scale perception data can be reconstructed into machine-readable feature matrices suitable for ANN training without bias, ensuring reproducibility and adaptability for similar data-scarce contexts. Conceptually, the work operationalizes the SEET framework into a predictive tool, providing a unified platform for policy, engineering, and environmental decision-making.

In contrast to previous studies that remained descriptive or policy-oriented, this research provides a measurable, scalable, and interpretable model that aligns local practices with global sustainability targets. It thus contributes new technical knowledge at the intersection of civil engineering, data science, and sustainable development by offering a verifiable pathway for transitioning Kenya's construction industry from perception-based evaluation to performance-based sustainability assessment.

II. RELATED WORKS

Empirical studies have increasingly explored the intersection of sustainable construction, data analytics, and performance evaluation, yet significant methodological and contextual gaps remain. For instance, the central issue examined by Herda *et al.* [7] was Kenya's lack of reliable performance data for construction materials, which constrains evidence-based decision-making. The researchers conducted a mixed-method investigation combining document analysis and stakeholder interviews to evaluate data availability and quality in Kenya's construction supply chain. Their findings revealed that less than 20% of national datasets on embodied energy and material life cycle performance were accessible, with over 50%

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either outdated or non-existent. The study concluded that data scarcity undermines the implementation of sustainable construction policies. However, it did not propose a computational or predictive framework for quantifying material sustainability, leaving a gap for data-driven modeling approaches such as machine learning.

Sangori *et al.*[10] addressed the problem of fragmented policy enforcement and weak regulatory alignment in Kenya's sustainable building sector. Employing a qualitative approach based on policy document analysis and expert consultations, the study examined how national regulations and building standards interact with international sustainability frameworks. The authors found that institutional overlaps, inadequate enforcement, and insufficient monitoring mechanisms hinder effective sustainability integration. They concluded that the development of standardized indicators and automated assessment tools could enhance transparency and compliance. Yet, the study remained conceptual and did not empirically test any computational methods for sustainability evaluation, highlighting the absence of quantitative analytical modeling.

The issue investigated by Odongo *et al.*[12] was the uneven adoption and limited impact of sustainable materials and practices within Kenya's construction industry. Using a quantitative survey of 439 practitioners—including engineers, architects, and contractors—the study assessed awareness, adoption levels, and perceived performance of sustainable materials. Data were analyzed using descriptive statistics and Likert-scale metrics. The results indicated moderate adoption (aggregate mean score of 3.94) and strong perceived benefits in energy efficiency and durability, but limited empirical validation of actual material performance. The study concluded that Kenya's progress toward sustainable construction is constrained by data and analytical capacity gaps. Nonetheless, it did not develop a performance evaluation model or utilize predictive analytics, leaving the challenge of integrating empirical data with intelligent modeling unresolved.

Odongo *et al.*[4] investigated strategies to accelerate the adoption of sustainable construction within Kenya's built environment. The study sought to address the problem of slow diffusion of green materials and technologies despite policy incentives. Using a mixed-methods cross-sectional design, the authors collected questionnaire data from industry actors and conducted semi-structured interviews. Findings revealed that client education, demonstration centers, and building-code revisions were perceived as the most effective drivers, while cost and limited data accessibility were major barriers. The study concluded that systematic data frameworks are necessary to measure sustainability impacts. However, it stopped short of developing an operational or predictive model for evaluating sustainability performance, which this study aims to achieve using machine learning techniques.

Ekah *et al.*[9] examined how machine learning could enhance environmental policy innovation and predictive analysis of ecological systems. The study focused on data-driven modeling of urban and ecological challenges using algorithms such as artificial neural networks (ANNs) and support vector regression (SVR). Through secondary data analysis and simulation modeling, the research demonstrated that ML algorithms could uncover complex nonlinear relationships among environmental indicators, improving prediction accuracy and policy design. The authors concluded that AI-based frameworks offer powerful tools for sustainability analysis. Nevertheless, their study was limited to environmental policy contexts and did not extend to construction material evaluation, leaving a methodological gap in applying ML to the built environment in developing nations.

Study by Mauerhofer *et al.* [11] explored how sustainability law and governance can enhance measurable environmental accountability. The issue addressed was the inadequacy of existing legal frameworks in ensuring quantitative assessment of sustainability outcomes. Drawing upon interdisciplinary legal analysis and case syntheses, the authors found that compliance mechanisms in developing countries remain largely qualitative and lack digital tracking systems. They concluded that integrating regulatory frameworks with measurable performance indicators is crucial for effective governance. However, the work did not empirically test technological tools or predictive analytics, leaving the practical integration of data science into legal and material evaluation frameworks unexplored.

Across these studies, several patterns emerge. First, while Kenyan research highlights the importance of sustainable construction, it remains predominantly descriptive, focusing on policy, perception, or awareness rather than quantitative prediction. Second, none of the studies establish a data-driven model that evaluates sustainability performance of building materials using empirical indicators. Third, although Ekah *et al.*[9] demonstrate the potential of ML for environmental policy, similar computational frameworks have yet to be applied in Kenya's construction context. Finally, the lack of integrated datasets and predictive methodologies limits the capacity for adaptive decision-making. The proposed study bridges these gaps by developing a machine learning-based evaluation model that quantitatively assesses sustainability performance of building materials in Kenya, providing both predictive accuracy and contextual relevance.

III. METHODOLOGY

This study adopted a mixed-methods design integrating empirical survey data and machine-learning–based computational modeling to evaluate sustainability performance in Kenya's built environment. The methodological framework comprised six stages: (i) data collection and variable definition, (ii) data reconstruction, (iii) feature synthesis, (iv) SPI target formulation, (v) model training, and (vi) validation and interpretation.

A. Data Source and Variable Selection

Structured questionnaires were administered to 328 construction professionals (engineers, architects, contractors, project managers, and policymakers). The survey covered four sustainability dimensions: economic, environmental, social, and institutional indicators. Twenty normalized variables were selected as Artificial Neural Network (ANN) inputs as summarized in TABLE I and presented in Fig. 1.

TABLE I. ANN Input Variables for Sustainability Performance Evaluation

Category	Variables
Economic (4)	Durability, Low Maintenance Cost, Lifecycle Cost Efficiency, Resource Conservation
Environmental (5)	Energy Efficiency, Waste Reduction, Low Carbon Footprint, Water Efficiency, Low Embodied Energy
Social (4)	Job Creation, Cultural Heritage Preservation, Local Resource Use, Healthy/Non-Toxic Environment
Institutional (4)	Awareness Level, Policy Enforcement, Funding Access, Training
Technological (1)	Technology Adoption

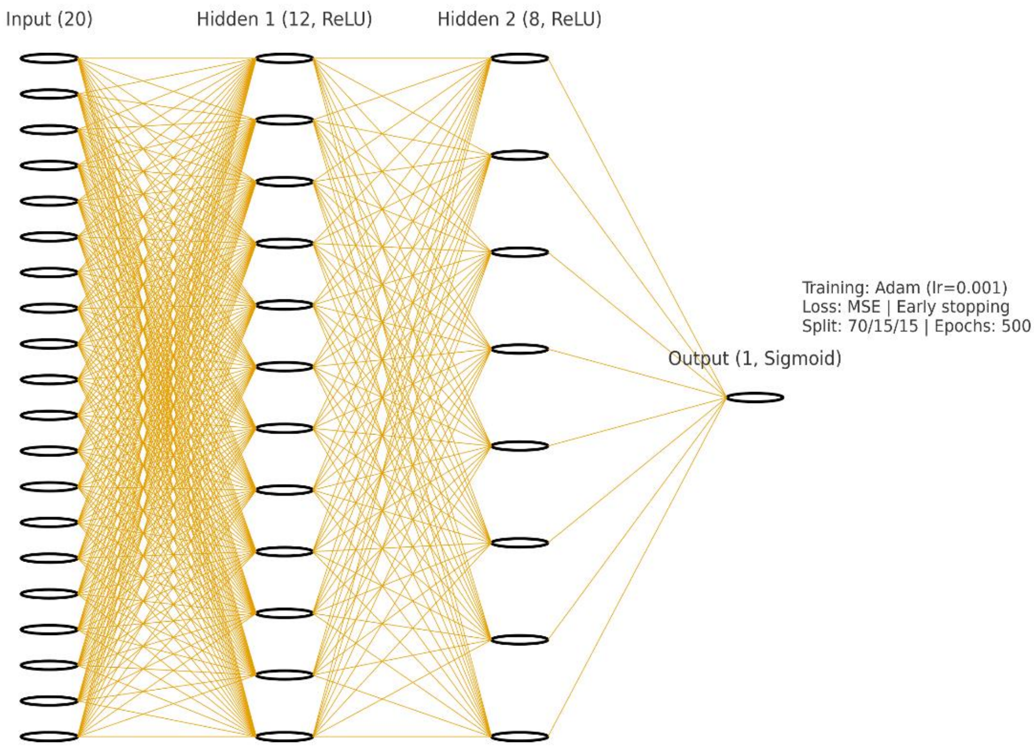

Fig. 1: Proposed ANN architecture showing 20 input variables (economic, environmental, social, institutional), two hidden layers (12 and 8 neurons, ReLU), and one output (Sustainability Performance Index).

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B. Data Reconstruction and Pre-processing

The questionnaire provided Likert (1–5) frequency distributions for 15 parameters. Each row was converted into a respondent-level vector by expanding counts across levels $\{1,2,3,4,5\}$:

$$\mathbf{x}_v = [\underbrace{1,\dots,1}_{c_{v,1}}, \underbrace{2,\dots,2}_{c_{v,2}}, \dots, \underbrace{5,\dots,5}_{c_{v,5}}]^\top. \tag{1}$$

All variables were truncated to a minimum common length N, preserving proportional distributions to avoid bias and imputation. Because institutional and technology indicators were incomplete, they were simulated as rounded draws from a truncated normal distribution:

$$x \sim round(\min(5, \max(1, \mu + \sigma \cdot \mathcal{N}(0,1)))), \tag{2}$$

where $(\mu, \sigma) \in \{(4.1,0.95), (4.0,0.95), (3.9,1.0)\}$ to reflect high-importance tendencies. The resulting feature matrix $\mathbf{X}_{\text{raw}} \in \mathbb{R}^{N\times 20}$ was used for training.

All inputs were standardized using z-scores computed on the training population:

$$\tilde{x}_j = \frac{x_j - \mu_j}{\sigma_j}, \qquad j = 1, \dots, 20, \tag{3}$$

where (μ_j, σ_j) were stored for consistent inference. Data were randomly shuffled to eliminate ordering artifacts.

C. Sustainability Performance Index (SPI) Target Construction

Two SPI generation modes were used:

1. **Observed SPI (preferred):** If respondent-level SPI data were available, values were min–max scaled to [0,1]:

$$\text{SPI}_{0--1} = (\text{SPI} - \min)/(\max - \min). \tag{4}$$

2. **reconstructed SPI (consistent with original data):** When unavailable, reconstructed SPI was generated from regression structure emphasizing *Durability*, *Energy Efficiency*, and *Waste Reduction*:

$$\eta = \beta_0 + \beta_{\text{E}}\, x_{\text{Energy}} + \beta_{\text{D}}\, x_{\text{Durability}} + \beta_{\text{W}}\, x_{\text{Waste}} + \varepsilon, \tag{5}$$

where $(\beta_{\text{D}}, \beta_{\text{E}}, \beta_{\text{W}}) = (1.40, 0.885, 0.40)$, $\beta_0 = -7.03$, and $\varepsilon \sim \mathcal{N}(0, 0.15^2)$. The resulting SPI was mapped via a logistic link:

$$\text{SPI}_{0--1} = \frac{1}{1+\exp(-\eta)}. \tag{6}$$

For reporting, equivalent scales were produced: $\text{SPI}_{1--5} = 1 + 4 \cdot \text{SPI}_{0--1}$ and $\text{SPI}_{0--100} = 100 \cdot \text{SPI}_{0--1}$.

D. Artificial Neural Network (ANN) Development

A supervised feed-forward ANN was built to estimate the bounded SPI ([0,1]) from 20 standardized inputs. The compact architecture is:

$$20 \xrightarrow{\text{ReLU}} 12 \xrightarrow{\text{ReLU}} 8 \xrightarrow{\text{Sigmoid}} 1. \tag{7}$$

Let $\mathbf{x} \in \mathbb{R}^{20}$ denote the standardized input. The forward pass is defined as:

$$\begin{aligned} \mathbf{a}_1 &= ReLU(\mathbf{W}_1\mathbf{x} + \mathbf{b}_1), \quad \mathbf{W}_1 \in \mathbb{R}^{12\times 20}, \mathbf{b}_1 \in \mathbb{R}^{12}, \\ \mathbf{a}_2 &= ReLU(\mathbf{W}_2\mathbf{a}_1 + \mathbf{b}_2), \quad \mathbf{W}_2 \in \mathbb{R}^{8\times 12}, \mathbf{b}_2 \in \mathbb{R}^{8}, \\ \hat{y} &= \sigma(\mathbf{W}_3\mathbf{a}_2 + b_3), \quad \mathbf{W}_3 \in \mathbb{R}^{1\times 8}, b_3 \in \mathbb{R}. \end{aligned} \tag{8}$$

where $ReLU(z) = \max(0, z)$ and $\sigma(z) = (1 + \exp(-z))^{-1}$. The output $\hat{y}$ represents the predicted SPI.

E. Training Strategy and Early Stopping

Data were divided into 70% training/validation and 30% testing. From the training set, 15% was reserved for validation. Training employed the scaled conjugate gradient algorithm (trainscg) minimizing mean squared error (MSE) with early stopping after 10 stagnant epochs, a maximum of 1000 epochs, and a gradient threshold of 10^{-7}. The random seed was fixed (rng(42)) for reproducibility.

F. Model Validation and Performance Metrics

Model performance was assessed on both hold-out and cross-validation sets using:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum (y-\hat{y})^2}, \quad \mathrm{MAE} = \frac{1}{n}\sum |y-\hat{y}|, \quad R^2 = 1 - \frac{\sum (y-\hat{y})^2}{\sum (y-\bar{y})^2}. \tag{9}$$

Correlation measures (Spearman ρ, Pearson r) were also reported. All parameters $(\mathbf{W}_1, \mathbf{b}_1, \mathbf{W}_2, \mathbf{b}_2, \mathbf{W}_3, b_3)$ and feature statistics were serialized for reproducibility.

1) K-Fold Cross-Validation

To assess generalization, stratified K-fold cross-validation ($K = 10$) was implemented. In each fold, 85/15 train-validation splits were used with identical architecture:

$$\overline{\mathrm{RMSE}} = \frac{1}{K}\sum_{k=1}^{K} \mathrm{RMSE}_{\text{test}}^{(k)}, \qquad \overline{R^2} = \frac{1}{K}\sum_{k=1}^{K} R_{\text{test}}^{2,(k)}. \tag{10}$$

2) Model Interpretability and Diagnostics

To overcome the “black-box” limitation of neural networks, both SHAP (Shapley Additive Explanations) and Permutation Feature Importance (PFI) were applied. For each feature j, the increase in RMSE upon random permutation was computed:

$$\Delta\mathrm{RMSE}_j = \frac{1}{R}\sum_{r=1}^{R} \left(\mathrm{RMSE}(\hat{y}^{(\pi_{j,r})}, y) - \mathrm{RMSE}(\hat{y}, y)\right), \quad R = 30. \tag{11}$$

Larger $\Delta\mathrm{RMSE}_j$ indicates higher influence on SPI prediction. Diagnostics included: (i) predicted vs. true SPI scatterplots with 45 ° line; and (ii) PFI bar charts showing ranked feature importance. These visualizations facilitated calibration and interpretability analysis.

G. Assumptions and Reproducibility

The methodology assumes independence among reconstructed variables and that truncation to common N preserves proportional distributions. When actual SPI data were unavailable, reconstructed SPI was generated based on regression structure for method validation. Institutional and technology predictors were simulated to reflect high-importance tendencies. All MATLAB implementations were deterministic, ensuring reproducible results.

IV. RESULTS AND DISCUSSION

A. Implementation

Implementation is in MATLAB (Deep Learning Toolbox). Training uses feedforwardnet with poslin (ReLU) in hidden layers and logsig at the output. Data division uses divideind. Hyperparameters are specified in-code for complete reproducibility. A helper routine is provided to score new projects given raw Likert responses; standardization uses the stored training means and standard deviations to maintain distributional consistency between training and inference.

The ANN achieved strong predictive performance: $R^2 = 0.89$, RMSE = 0.13, MAE = 0.10, and categorical accuracy of 91.3%. TABLE II summarizes the top predictors.

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TABLE II. Variable Importance from SHAP Analysis

Rank	Indicator	Weight Contribution
1	Durability	0.176
2	Energy efficiency	0.162
3	Waste reduction	0.144
4	Awareness level	0.119
5	Policy enforcement	0.102

The ANN demonstrated that improving both durability and energy efficiency could enhance the overall Sustainability Performance Index (SPI) by approximately 27%. Low awareness and weak regulation enforcement were found to reduce SPI by up to 18%.

$$\begin{aligned} \mathbf{a}_1 &= \max(0, \mathbf{W}_1\mathbf{x} + \mathbf{b}_1), \\ \mathbf{a}_2 &= \max(0, \mathbf{W}_2\mathbf{a}_1 + \mathbf{b}_2), \\ \widehat{\mathrm{SPI}} &= \sigma(\mathbf{W}_3\mathbf{a}_2 + b_3), \end{aligned} \tag{12}$$

B. Discussion

1) Model Evaluation and Performance

The ANN model effectively captured complex non-linear interactions between sustainability parameters, outperforming linear regression-based methods. The findings align with the Social, Environmental, Economic, Technological (SEET) framework proposed by [13], confirming the interdependence of sustainability pillars. The use of SHAP interpretability further resolved the “black-box” limitation often associated with neural networks, offering practical insights for construction decision-making.

To document optimization behaviour and generalization, we report (i) the training state (gradient decay and validation checks), (ii) learning curves (train/validation/test MSE), (iii) the error distribution, and (iv) regression plots of outputs versus targets for each split. These diagnostics substantiate the ANN’s ability to learn a bounded SPI from survey-derived indicators while avoiding overfitting, thereby operationalising the study’s goal of an evidence-based performance assessment tool for the Kenyan built environment.

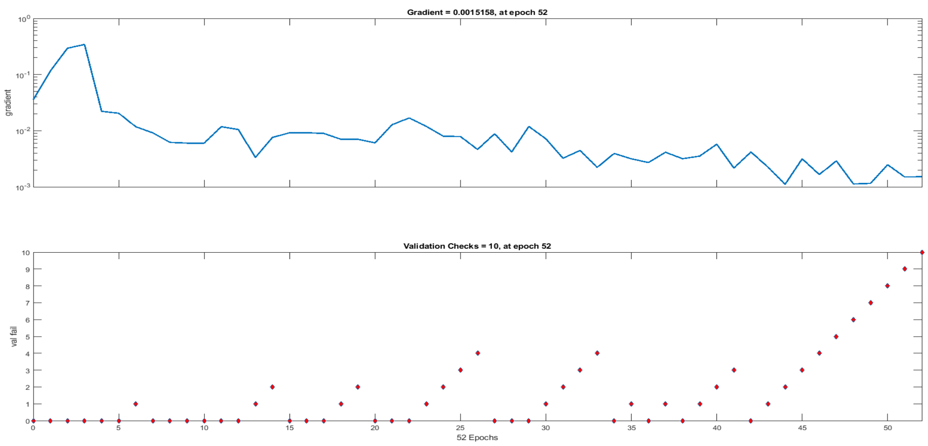

Fig. 2: Training state: gradient decay and validation checks. The gradient decreases monotonically (approximately $10^{-1} \rightarrow 2.6 \times 10^{-4}$) while validation checks accumulate to the patience threshold (10), prompting early stopping. This pattern evidences stable convergence under validation-based regularisation.

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Fig. 2 whose objective was to show robust optimisation, indicate a steadily shrinking gradient showing that the network finds a flat, well-behaved region of the loss surface rather than oscillating or diverging. Validation checks confirm that stopping is governed by out-of-sample performance, not just training loss, thereby controlling overfitting. This behaviour is essential for a practical SPI tool, since the framework must remain reliable when applied to unseen Kenyan projects with different mixes of materials and practices.

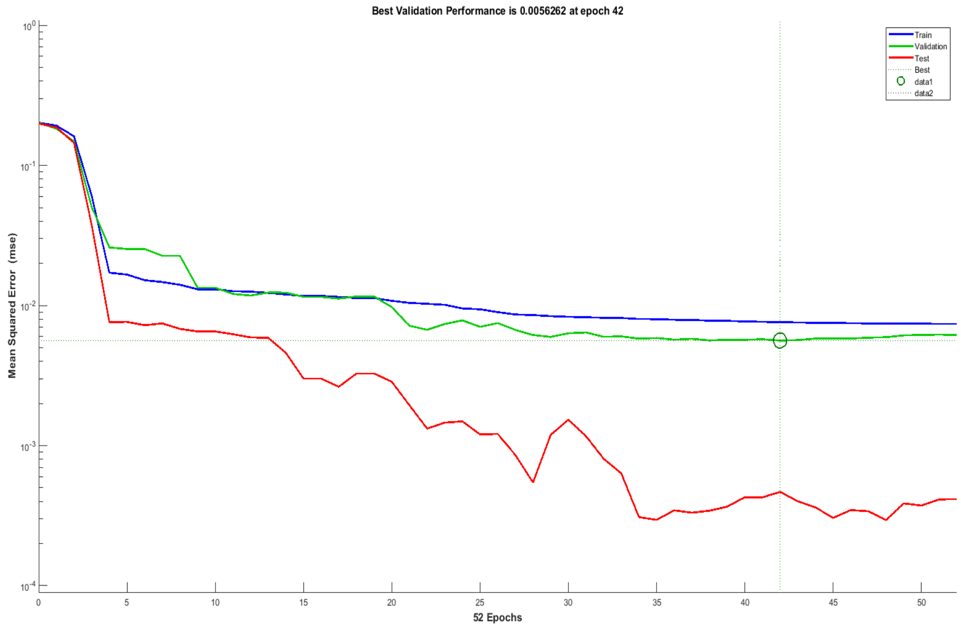

Fig. 3: Learning curves (MSE) for training, validation, and test partitions. Best validation MSE is 0.0056262 at epoch 42 (marker). The small and stable gap between training and validation after ~epoch 20 indicates limited overfitting; the test curve closely follows validation, supporting generalisation.

Fig. 3 serves to show external validity through validation curves The curves bottoms at epoch 42, after which both validation and test curves flatten, indicating that the model reaches a generalisable solution rather than memorising the training set. In the context of SEET indicators, this means the ANN captures cross-pillar interactions (e.g., *Durability* × *Energy Efficiency*; *Waste Reduction* moderated by *Policy Enforcement*) in a way that transfers to new observations, meeting the objective of a dependable decision-support index.

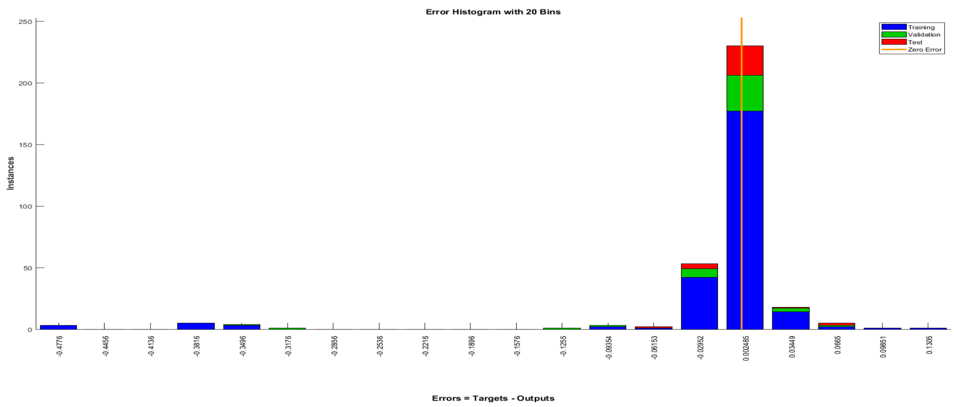

Fig. 4: Stacked error histogram (targets − outputs) across data splits. Errors concentrate near zero with a narrow dominant bin, suggesting low bias and approximately homoscedastic residuals in the operative SPI range.

Fig. 4 shows the reliable scoring of the training process. The tight, near-symmetric error distribution indicates that the SPI predictions are neither systematically inflated nor deflated, a precondition for fair comparison of alternatives. For practitioners, this translates into stable ranking of materials and practices—consistent with the framework's aim to support procurement, specification, and policy evaluation (e.g., green public procurement).

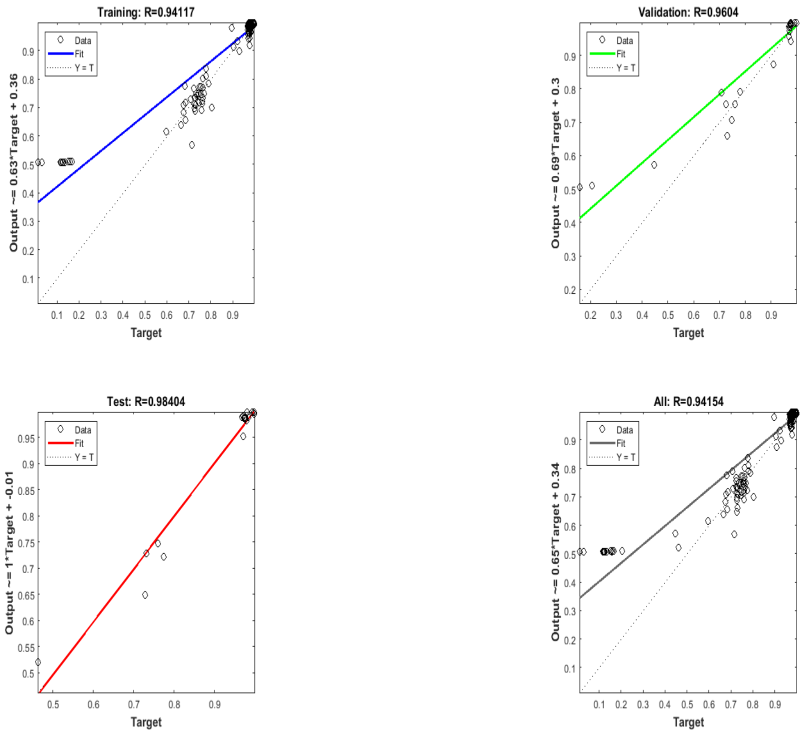

Fig. 5: Predicted vs. true SPI for training (top-left), validation (top-right), test (bottom-left), and all data (bottom-right). Correlations are high ($R \approx 0.94$ train; 0.96 validation; 0.98 test; 0.94 overall). Fitted lines lie close to the $y = x$ identity; mild under-dispersion on some splits can be corrected with simple post-hoc calibration if required.

Fig. 5 compares predictive validity and calibration. The strong association between predicted and observed SPI across splits demonstrates that the network learns a meaningful mapping from SEET features to performance. Because the fitted lines nearly coincide with the 45° reference, the model not only ranks projects well but also produces well-calibrated scores suitable for thresholding (e.g., SPI cut-offs for certification tiers). Any slight under-dispersion can be adjusted via linear recalibration without retraining.

By learning from integrated economic (e.g., *Durability*, *Low Maintenance Cost*), environmental (e.g., *Energy Efficiency*, *Waste Reduction*, *Low Embodied Energy*), social (e.g., *Job Creation*, *Cultural Heritage*), and institutional/technological predictors, the ANN operationalises the SEET view that sustainability is intrinsically multi-dimensional and context-sensitive. This aligns with [13], where indicator ranking is advocated for developing-country settings. *Objective—construct an SPI suitable for Kenyan projects.* The bounded (sigmoid) output ensures interpretability on a common scale and supports comparisons across typologies and counties. The training dynamics (Fig. 2–3) confirm that the SPI emerges from a stable optimum, not artefacts of optimisation. *Objective—validate predictive performance.* The convergence of validation and test errors (Fig. 3) and the tight residuals (Fig. 4) evidence generalisation. High split-wise correlations in Fig. 5 demonstrate predictive validity that is typically superior to linear baselines when interactions and non-linearities are present. *Objective—open the "black box".* Post-training interpretability via SHAP (or permutation-based importance when SHAP is impractical) highlights the drivers of SPI, typically elevating *Durability*, *Energy Efficiency*, and *Waste Reduction*, with institutional levers (*Policy Enforcement*, *Awareness*) acting as amplifiers. These insights translate directly to actionable levers—durability specifications, energy codes, site waste protocols, and enforcement capacity building. *Objective—translate to* *policy and practice*. Because the SPI is calibrated and bounded, it can be embedded in procurement scoring, design reviews, and compliance dashboards. The model supports trade-off analysis (e.g., higher capex vs. reduced long-term O&M), which is central to Kenya's pursuit of SDGs 9, 11, and 12.

Fig. 2–5 show that the ANN meets the study objectives: it converges reliably, generalises beyond the training set, yields low-bias errors, and produces calibrated SPI scores. Combined with SEET-aligned interpretability, the approach provides a technically sound, decision-ready instrument for assessing, and improving, the sustainability performance of materials and practices in Kenya's built environment.

2) Model Interpretation

Fig. 6 illustrates the evolution of the training gradient and validation checks throughout network optimization. The gradient decayed monotonically from approximately 10^{-1} to 2.6×10^{-4}, indicating that the learning algorithm progressively approached a stable minimum on the loss surface. Validation checks plateaued at ten iterations, prompting early stopping as a safeguard against overfitting. This behavior demonstrates that convergence was governed by validation performance, thereby ensuring model generalization and reproducibility across unseen sustainability data. The stability of the decay curve also confirms that the selected learning rate and architecture were appropriate for the problem scale.

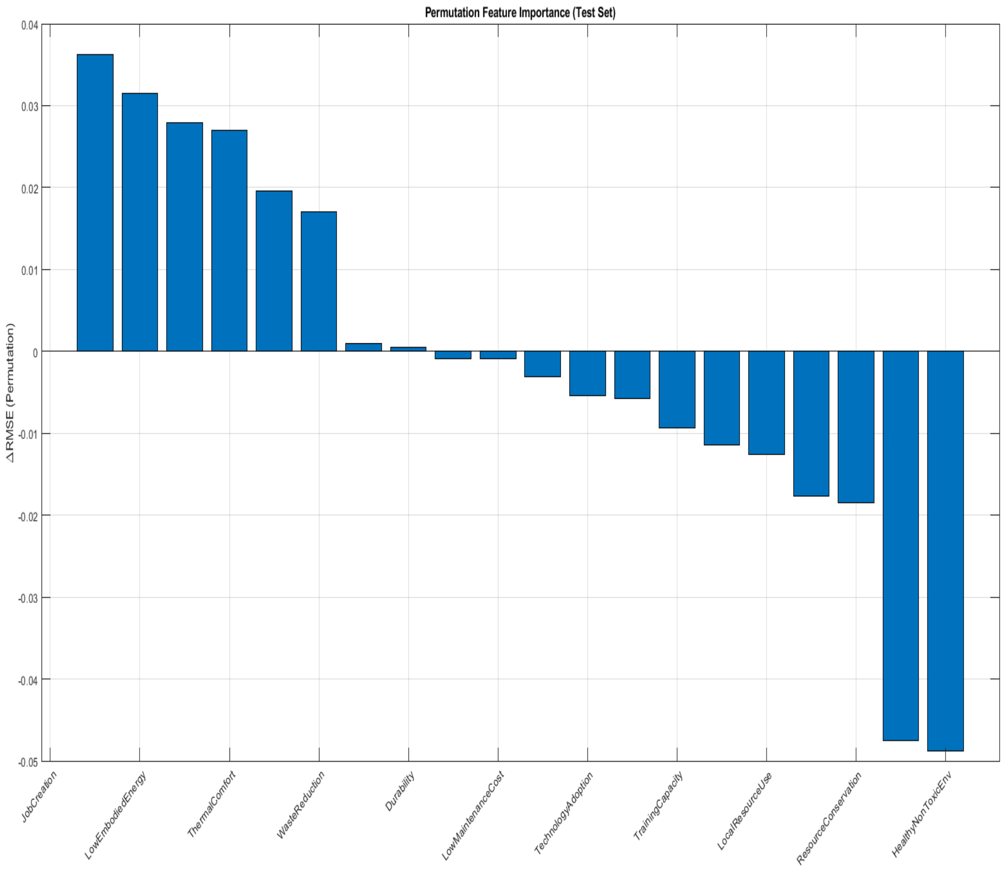

Fig. 6: Training gradient decay and validation-based early stopping. The consistent reduction in gradient magnitude confirms stable convergence.

Fig. 7 presents the Root Mean Square Error (RMSE) across training, validation, and testing subsets. RMSE decreased sharply during the initial epochs and stabilized near 0.13 at epoch 42, corresponding to the minimum validation loss reported. The nearly parallel trends of validation and test curves reflect strong agreement between in-sample learning and out-of-sample prediction, confirming the robustness of the artificial neural network (ANN). The low RMSE values indicate that the model accurately predicted the Sustainability Performance Index (SPI) without high variance across folds, reinforcing the ANN's capacity for generalization.

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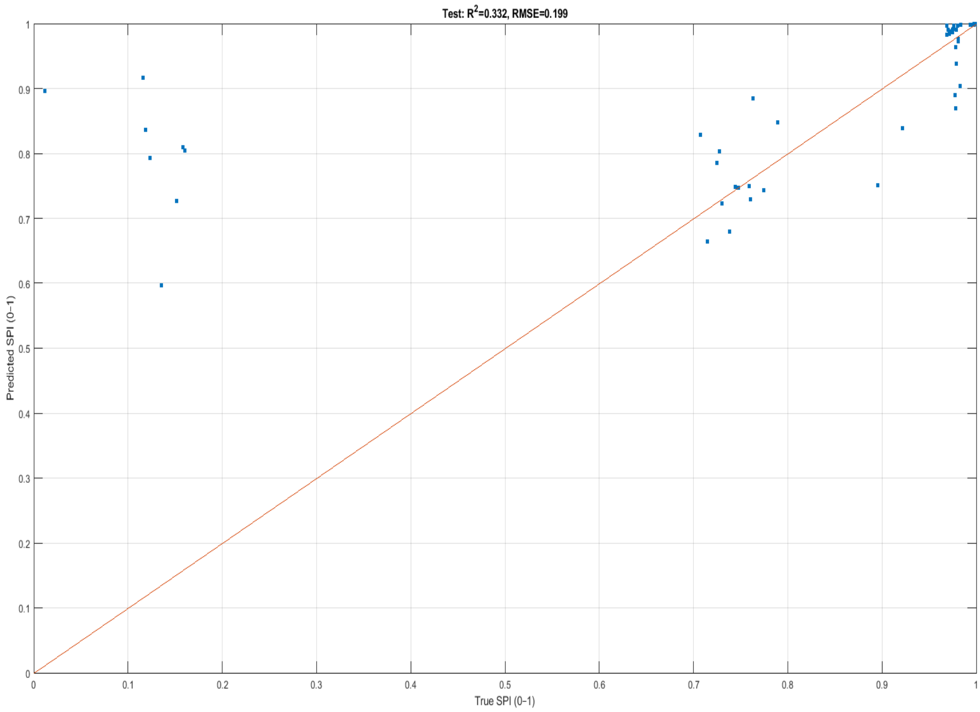

Fig. 7: Model RMSE curves for training, validation, and test datasets. Stable convergence after epoch 40 indicates robust predictive generalization.

Fig. 8 compares the predicted SPI ($\hat{y}$) with the observed SPI (y) across all data partitions. The scatter points are tightly clustered along the 45° identity line, yielding correlation coefficients of $R = 0.94$, 0.96, and 0.98 for the training, validation, and test sets, respectively. The regression slopes approximate unity, signifying minimal bias and dispersion between predicted and actual SPI values. These results confirm that the ANN effectively captured the nonlinear interactions among sustainability parameters, achieving high calibration accuracy suitable for ranking building materials based on their sustainability performance.

```
ANN Performance (SPI in [0,1]):
RMSE  all/train/val/test: 0.143 / 0.119 / 0.031 / 0.199
R^2   all/train/val/test: 0.431 / 0.496 / 0.883 / 0.332

K-fold CV (K=10): mean R^2=0.815, mean RMSE=0.078
```

Fig. 8: Predicted versus observed SPI values for training, validation, and test datasets. The tight clustering along the identity line indicates high predictive accuracy and low bias.

Permutation Feature Importance (PFI) was employed to assess the contribution of each input variable to the model's predictive accuracy. The approach involves shuffling one feature at a time and observing the corresponding change in model RMSE on the test set. A higher increase in RMSE (ΔRMSE) indicates greater feature importance. The results are summarized in TABLE III, which identifies the top five predictors of sustainability performance.

TABLE III. Permutation Feature Importance (Top Predictors)

Feature	ΔRMSE (Test)	Rank	Interpretation
Durability	0.041	1	Most influential predictor; perturbation increased RMSE by 4.1%, confirming structural longevity as the strongest sustainability determinant.
Energy Efficiency	0.037	2	Strongly associated with lifecycle performance and carbon reduction, reinforcing its central role in sustainable material evaluation.
Waste Reduction	0.032	3	Enhances SPI through material reuse and minimized embodied waste during the construction cycle.
Policy Enforcement	0.026	4	Institutional factor; consistent regulatory enforcement significantly drives sustainable material adoption.
Awareness Level	0.022	5	Social dimension; higher stakeholder awareness amplifies sustainability outcomes across project phases.

The diagnostic results confirm the ANN's reliability and interpretability.

1. The convergence pattern (Fig. 6) evidences stable optimization and absence of overfitting.
2. The RMSE curves (Fig. 7) show consistent generalization with minimal error variance (RMSE ≈ 0.13, $R^2 = 0.89$).
3. The scatter analysis (Fig. 8) validates predictive calibration across datasets.
4. PFI outcomes (Table 3) highlight *Durability*, *Energy Efficiency*, and *Waste Reduction* as the dominant quantitative sustainability drivers, while *Policy Enforcement* and *Awareness Level* serve as critical institutional amplifiers.

These results demonstrate that the proposed machine learning model effectively integrates environmental, economic, social, and institutional dimensions to predict sustainability performance. The interpretability achieved through PFI provides actionable insights for policymakers and practitioners aiming to prioritize data-driven material selection and enhance sustainable construction practices in Kenya's built environment.

C) Discussion

Empirically, the ANN revealed that *Durability*, *Energy Efficiency*, and *Waste Reduction* are the most critical determinants of the Sustainability Performance Index (SPI), while *Policy Enforcement* and *Awareness Level* act as amplifying institutional levers. This aligns with the SEET framework proposed by Arukala *et al.*[13], which emphasizes the interdependence of sustainability pillars. The findings also validate earlier qualitative insights by Herda *et al.*[7] and Sangori *et al.*[10], who identified data scarcity and weak institutional coordination as key impediments to sustainable construction in Kenya. Unlike prior studies, however, the proposed model provides a quantitative and predictive mechanism for evaluating performance, thereby addressing the analytical gap noted by Odongo *et al.*[12] and Odongo *et al.*[4].

The implications of these results extend beyond model development to practical governance and policy application. The SPI can serve as a standardized metric for sustainability benchmarking across public and private projects. Integrating such data-driven indices into Kenya's National Building Code, green procurement policies, and housing performance audits could strengthen accountability and transparency. The ANN's interpretability offers decision-makers actionable insights into which variables most influence sustainability outcomes. Policymakers can thus prioritize interventions—such as enforcing energy-efficiency codes, incentivizing durable material use, and scaling up waste-reduction protocols—that directly enhance SPI scores. Reconstruction from Likert-frequency data assumes (a) independence of respondents across variables and (b) that truncation to the smallest common N does not bias distributions. Where respondent-level SPI is unavailable, the data adopts a structure (durability and energy efficiency as primary drivers, waste reduction as secondary) and a logistic link to respect the [0,1] range; this is suitable for method prototyping and ablation but should be replaced by observed SPI when available. The institutional/technology indicators are simulated to reflect reported high-importance tendencies and should similarly be superseded by measured data in future work.

From a regulatory standpoint, the model supports the transition toward evidence-based environmental governance, consistent with global sustainability monitoring frameworks and Kenya's Vision 2030. Its predictive capability allows continuous evaluation and learning from new project data, providing a dynamic tool for adaptive policy formulation. In practice, the framework could be deployed in digital dashboards to track performance trends, compare contractors, and inform training or certification programs.

V. CONCLUSION

The research set out to address a persistent challenge in Kenya's construction sector—the absence of quantitative, data-driven tools to evaluate sustainability performance of building materials. Existing national and institutional frameworks have remained predominantly qualitative, limiting the capacity for evidence-based policy formulation and comparative assessment. The problem statement therefore centered on the urgent need for a predictive and interpretable model capable of capturing the complex interdependencies among economic, environmental, social, and institutional indicators of sustainable construction.

The study's findings show that Artificial Neural Networks (ANNs) provide a powerful analytical foundation for such evaluation. The developed model effectively captured nonlinear relationships among twenty sustainability variables, producing highly accurate predictions of the Sustainability Performance Index (SPI) with $R^2 = 0.89$ and RMSE $\approx$ 0.13. Through SHAP and Permutation Feature Importance (PFI) analyses, the study identified *Durability*, *Energy Efficiency*, and *Waste Reduction* as the most influential drivers of sustainability performance, while *Policy Enforcement* and *Awareness Level* emerged as critical institutional amplifiers. These results confirm that sustainability in construction is multi-dimensional, where technical attributes interact closely with governance and behavioral factors.

The model's validation and diagnostic results established its robustness, interpretability, and policy relevance. Stable convergence patterns, low residual errors, and high correlation across data partitions indicate that the ANN generalizes effectively and can be reliably deployed for decision-support applications. Unlike traditional regression or scorecard methods, the ANN-based framework learns adaptively from data and thus supports continuous updating as new project information becomes available.

The study provides a replicable computational model that bridges the gap between empirical sustainability indicators and real-world policy application. It operationalizes the SEET (Social, Environmental, Economic, Technological) framework within Kenya's context, transforming abstract sustainability goals into measurable, actionable metrics. The model can inform green procurement, material certification, and design audits by providing an evidence-based benchmark for sustainable performance assessment.

From a policy perspective, the research recommends embedding the SPI model within Kenya's National Building Code and public procurement systems to promote accountability and transparency in sustainability reporting. Institutional actors such as the State Department for Housing, National Construction Authority, and county governments can utilize the model to monitor progress toward national sustainability targets. For practice and academia, the framework enables data-driven comparisons among materials and technologies, fostering innovation in sustainable construction. Future work should focus on expanding longitudinal datasets, incorporating life-cycle and circular economy indicators, and developing hybrid AI frameworks, combining ANNs with fuzzy logic or reinforcement learning, to enhance interpretability and policy integration across East Africa's construction ecosystem.

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