

Strength-Driven Inverse Modelling Of Agricultural Waste Concrete Using Feasibility-Guided Generative Intelligence Operations

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Abstract: Rice husk ash and corn cob derivatives are popular in sustainable concrete systems, but the lack of dependable, performance-driven mix design procedures limits their use in structural applications. Most existing processes adjust mix proportions to desired strengths using forward prediction models or laborious trial-and-error methods. Such methods struggle with the inverse nature of real engineering issues, where compressive, tensile, and flexural strength needs are set and mix composition must obey material, durability, and sustainability constraints. The diversity of agricultural waste materials and the ill-posedness of this inverse problem make present design solutions unreliable. This study introduced a strength-driven inverse modeling method for agricultural waste concrete that handles mix design as a limited inverse job. A pipeline with five tightly coupled analytical modules is proposed. A Strength-Conditioned Mix Manifold Learning (SC-MML) module learns a continuous, constraint-aware latent representation of viable concrete mixes conditioned on goal mechanical attributes to assure initial physical plausibility. A Pareto Inverse Solver with Feasibility-Gated Diffusion (PIS-FGD) generates many candidate mix designs that meet strength, workability, and embodied carbon criteria from this manifold. A Microstructure-Consistent Forward Twin with Material Tokens (MiC-FTMT) assesses candidate mixes using rice husk ash and corn cob property descriptors to ensure hydration and porosity consistency and increase generalization across agricultural waste sources. To reduce shortcut learning and cement reliance, the Causal Robustness and Counterfactual Mix Auditing (CR-CMA) stage stress-tests mixes under controlled interventions. Finally, CL-ALV-BER refines inverse and forward models utilizing residuals from experimental input sets. The framework maintains structural performance with high objective fidelity, minimum design iterations, and cement substitutions. Accurate inverse mix designs and a systematic methodology for performance-centric, low-carbon concrete engineering enable confident use of agricultural waste materials in structural-grade applications and advance civil engineering inverse materials designs.

Keywords: Inverse Mix Design, Agricultural waste Concrete, Strength-Constrained Optimization, Generative Modelling, Sustainable Construction Materials, Scenarios.

1. Introduction

Concrete is the most common construction material for transportation, housing, and industry [1, 2, 3]. This broad use is environmentally costly due to cement manufacturing, which emits a lot of carbon dioxide. Over the past two decades, research has increased into cementitious materials and reinforcements made from industrial and agricultural waste. Due to their high silica content, pozzolanic activity, low embodied energy, and widespread availability in rural economies, rice husk ash and corn cob derivatives appear promising. Despite its technological promise, mix design reliability and performance predictability difficulties limit agricultural waste materials in structural-grade concrete. Traditional concrete mix design is innovative. After choosing material proportions, compressive, tensile, and flexural strength sets are estimated experimentally or statistically. Due to raw material variability, processing condition sensitivity, and substantial nonlinear interactions among mix variables, adding agricultural waste complicates this process. Current methods employ trial-and-error experimentation or isolated optimization techniques, which are time-consuming, material Intensive, and

unscalable. Even newer machine learning-based studies typically use forward prediction models to infer strength from mix compositions, which is limited for practical engineering scenarios with specified performance objectives. The structural engineering design task is reversed. Engineers must establish suitable material compositions that meet design code performance [7, 8, 9], serviceability, safety margins, constructability, durability, and sustainability limitations. Inverse mapping agricultural waste materials is problematic since many mix combinations have identical strengths and tiny material property changes can cause disproportionate performance differences. If inverse optimization methods lack physical feasibility assurances, they may produce theoretically optimal but unbuildable or cement-dependent solutions. New generative modeling, latent manifold learning, and causal inference enable performance-first concrete mix design. Learning constraint-aware representations of possible mix spaces and embedding strength targets directly into the design process permits systematic generation of candidate compositions that achieve several mechanical criteria while decreasing environmental impact. Such approaches have not yet been cohesively applied to agricultural waste concrete systems or integrated with robustness analysis and experimental feedback mechanisms essential for engineering adoptions. A strength-driven inverse modeling framework for agricultural waste concrete employing rice husk ash and maize cob derivatives is proposed in this study. Instead of adding sustainability, the suggested approach embeds material replacement strategies into a carefully controlled inverse design pipeline to consistently infer mix proportions from mechanical performance. This study uses data-driven intelligence, physical feasibility, causal robustness, and laboratory validation to bring agricultural waste concrete from exploratory research to structural applications.

1.1 Motivation and Contributions

This attempt is driven by a fundamental gap between how concrete is made in practice and how most literature models it for different scenarios. Real-world design problems are driven by strength, durability, and sustainability, but most methods especially those using agricultural waste are reactive and forward-looking. Due to structural performance benchmark issues, this mismatch reduces material consumption and encourages alternative binders and reinforcements. Regression-based or heuristic optimization methods are inappropriate for robust inverse design because rice husk ash and corn cob-based materials are Variable In Process. Thus, a framework that directly addresses the task's inverse nature while regulating feasibility, robustness, and experimental uncertainty is needed for the process.

Many important contributions to that goal are in this work. It starts with a strength-conditioned inverse design paradigm that treats agricultural waste concrete mix design as a restricted inverse mapping issue with compressive, tensile, and flexural strength targets. Second, it generates numerous Pareto-optimal mix designs instead of one deterministic solution using latent manifold learning and diffusion-based inverse optimization in a feasibility-aware generative pipeline. Third, it generalizes across agricultural waste quality and processing conditions using rice husk ash and corn cob derivative material-specific descriptors in a microstructure-consistent forward twin. Fourth, causal robustness analysis through counterfactual auditing prevents designs from using cement content to boost strength. Active laboratory validation and Bayesian error recycling refine inverse and forward models using experimental feedback to close the design loop. These contributions provide a performance-centric sustainable concrete design paradigm beyond expected accuracy. The strategy reduces design iterations, material waste, and promotes confidence in employing agricultural waste in load-bearing applications. This work shows how strength-driven inverse modeling may be operationalized in a realistic engineering workflow to lay the framework for analytically

robust, practically deployable Next Generation, low-carbon concrete design methodologies.

2. Review of Existing Models used for Analysis

Decarbonization and waste valorization have increased agricultural waste use in construction materials research in the previous two years. Early research in this period uses forward-design approaches to turn agricultural wastes into cementitious systems. Kannur et al. [1] shown that appropriately proportioned rice husk ash-blended self-consolidating concrete for stiff pavements can meet severe rheological and strength requirements. Panda et al. [2] saw agricultural waste as a cyclic bioeconomy resource, highlighting waste streams' cross-sector potential. In Oyebisi's critical risk evaluation [3], radioactive exposure concerns in recycled agro industrial waste underlined the need for regulated material characterization rather than indiscriminate substitution sets. We went from feasibility to performance modeling and durability. Raheel et al. [4] reported nonlinear strength trends in concrete with agro industry wastes as cement substitutes depending on replacement level and curing regime. Permeability and hostile environment resistance were stressed in ternary blended systems using rice husk ash and sugarcane bagasse ash by Nadgouda and Sharma [5]. With data-driven models, Alnadish et al. [6] optimized compressive and tensile strength, proving machine learning's potential sets.

Table 1. Model's Empirical Review Analysis

Reference	Method	Main Objectives	Key Findings	Limitations
[1]	Experimental SCC with RHA	Develop self-consolidating concrete using rice husk ash for pavements	Demonstrated improved flowability and adequate strength with RHA replacement, enabling eco-friendly rigid pavements	Forward mix design; limited inverse control over target strength
[2]	Agricultural waste biopolymer valorization framework	Assess agro-food waste conversion into biopolymers	Established circular bioeconomy potential and waste-to-wealth pathways	Not construction-specific; lacks structural performance linkage
[3]	Risk assessment of agricultural waste reuse	Identify radioactive risks in recycled agro Industrial waste	Highlighted potential radiological exposure risks requiring material screening	Does not provide mitigation or design strategies
[4]	Experimental + regression modeling	Model strength behavior of agricultural	Captured nonlinear strength trends with agricultural	Predictive only; inverse design not addressed

		waste concrete	waste substitution	
[5]	Durability-focused ternary blending	Improve durability using RHA and bagasse ash	Enhanced resistance to permeability and aggressive environments	Optimization limited to predefined blends
[6]	ML-based strength optimization	Optimize compressive and tensile strength using waste powders	Achieved high predictive accuracy using ML models	Forward optimization; iterative trial-based tuning
[7]	Geopolymer concrete experimentation	Evaluate agricultural waste ash replacement in geopolymer systems	Confirmed mechanical viability of partial agricultural waste substitution	Narrow material scope; no design generalization
[8]	Non-destructive testing (NDT)	Evaluate strength using NDT for agricultural waste concrete	Correlated NDT indices with strength performance	Indirect evaluation; sensitive to calibration
[9]	ML regression for bricks	Predict compressive strength of agricultural waste bricks	Demonstrated ML suitability for sustainable masonry units	Limited to compressive strength only
[10]	Fineness-based experimental study	Study effect of agricultural waste fineness on AAB performance	Identified strong microstructure–fineness–strength coupling	Requires fine material characterization
[11]	Life Cycle Assessment (LCA)	Quantify environmental impacts of agricultural waste concrete	Showed significant CO ₂ reductions in permeable pavements	Does not integrate performance-driven design
[12]	Structural beam testing	Assess flexural behavior of agricultural waste concrete beams	Validated load-carrying capacity and crack behavior	Case-specific geometry; no generalized design model

[13]	Pervious concrete experimentation	Develop pervious concrete for water quality enhancement	Improved permeability and filtration performance	Strength-performance trade-offs not optimized
[14]	Lightweight AAC block development	Produce lightweight binder blocks using agricultural waste	Achieved reduced density with acceptable strength	Application-specific; limited structural use
[15]	Statistical strength analysis	Assess corn cob ash in concrete	Identified optimal replacement ranges statistically	Lacks mechanistic explanation
[16]	Thermal and CO ₂ performance study	Reduce CO ₂ and enhance thermal properties of bricks	Achieved major emission reduction and insulation benefits	Not focused on structural concrete
[17]	Torsional beam testing	Evaluate torsional strength with agricultural waste ash	Demonstrated acceptable torsional resistance	Limited loading scenarios
[18]	ML-based durability prediction	Predict strength and durability using biomedical waste ash	Improved prediction accuracy across durability metrics	Model dependent on dataset quality
[19]	Fiber-reinforced AAC experimentation	Enhance strength using steel fibers and agricultural waste	Improved ductility and post-cracking behavior	Increased material complexity
[20]	Paver block optimization	Improve strength and durability of paver blocks	Achieved enhanced abrasion and strength properties	Limited to paving applications
[21]	Material characterization study	Analyze agro marine waste ash properties	Provided detailed chemical and mineralogical profiles	No direct performance modeling

[22]	AI-based compressive strength modeling	Predict strength of marble-waste concrete	High accuracy achieved with AI-driven models	No inverse design capability
[23]	Microstructural durability analysis	Study RHA concrete with polymer inclusion	Improved durability and microstructure refinement	Material-specific conclusions
[24]	Statistical fiber optimization	Optimize bamboo and jute fiber concrete	Identified statistically significant fiber effects	Lacks predictive generalization
[25]	Comprehensive valorization review	Review agricultural waste utilization trends	Mapped emerging applications and research directions	Conceptual; no quantitative modeling
[26]	Electrical grounding application	Evaluate biochar as grounding backfill	Improved grounding resistance performance	Non-structural application
[27]	Geopolymer sustainability analysis	Assess slag-bagasse ash geopolymer concrete	Demonstrated strength-sustainability balance	Requires alkali activation control
[28]	Hybrid waste concrete study	Combine recycled aggregates, fibers, and fly ash	Achieved acceptable mechanical performance	Increased design dimensionality
[29]	Embodied carbon assessment	Study metakaolin and bagasse ash concrete	Reduced embodied carbon with maintained strength	Material availability constraints
[30]	ML-based optimization with banana leaf ash	Predict and optimize strength using ML	Improved prediction accuracy and optimization efficiency	Still forward-oriented; inverse mapping absent

Iteratively, Next, as per table 1, Next, Adisa et al. [7] evaluated agricultural waste ashes in geopolymer systems. These methods predicted effectiveness but were forward-looking and required multiple tries to reach target strength levels. Alternative performance measurements and non-destructive evaluation were discussed. Obianyo et al. [9] projected compressive strength of agricultural waste-stabilized bricks using machine learning, while Nadgouda and Sharma [8] tested agricultural waste concrete with manufactured sand non-destructively. Alkali-activated binders depend on agricultural waste fineness, according to Ganesh Adithya and Ponnambalam [10]. Microstructural factors affect performance. In agricultural waste-based alkali-activated concrete life cycle

assessment, Marathe et al. [11] quantified material selections and environmental impact. On concrete beams and pervious concrete, Madhavan et al. [12] and Phatkar et al. [13] proved that agricultural waste materials can meet functional demands above compressive strength sets Literature focused on hybrid and specialized materials. Ganta et al. [14] studied lightweight alkali-activated binder blocks made from industrial and agricultural waste, whereas Kesarwani [15] used statistics to support corn cob ash sustainability claims. Singh et al. [16] integrated agro-forestry waste with building and demolition debris, resulting in significant CO₂ savings and enhanced thermal performance. Krishnan and Subramanian [17] evaluated torsional strength in agricultural waste ash reinforced concrete beams under complicated load and found that agricultural waste concrete is approaching structural application. Although material variety expanded, the prevailing analytical framework persisted. Process study on biomedical waste ash, steel fiber reinforced alkali-activated systems, and sustainable paver blocks [18–20]. Forward testing and regression-based predictions characterized agromarine waste ash [21]. Kazemi and Mirjalili's waste marble concrete modeling [22] improved forecast accuracy but required mix adjustment. Statistical fiber-reinforced concrete [24], microstructural durability [23], and total valorization [25] showed agricultural waste system complexity. Perimeter applications such biochar grounding systems [26] and geopolymer concretes using slag and bagasse ash [27] highlighted agricultural waste materials' flexibility but flawed design rationale. Recent studies on recycled aggregates and fibers [28], hybrid metakaolin-bagasse ash systems [29], and machine learning-optimized banana leaf ash [30] demonstrate forward prediction and optimization best practices. Although engineering demands inverse, target-driven solutions, mix design has traditionally been considered a forward or trial-and-error endeavor. The field naturally evolves to strength-driven inverse modeling. Integrating strength targets, feasibility limits, and sustainability goals into the design process addresses the reviewed research's limitations. They combine the experimental results of early feasibility studies [1], [4], [5], the predictive breakthroughs of machine learning research [6], [9], [22], [30], and the environmental imperatives of life cycle and valorization assessments [11], [16], [25]. This material requires inverse design. These 30 papers characterize agricultural waste concrete research's maturity and the methodological inflection point where performance-driven inverse design is needed to transfer sustainability research into dependable engineering practices.

3. Proposed Model Design Analysis

The integrated model for agricultural waste concrete mix design generates, evaluates, and modifies material compositions using mechanical performance targets. The idea came from the fact that strength-governed concrete design is inverse and ill-posed, especially with heterogeneous agricultural waste like rice husk ash and corn cob derivatives. Beginning with figure 1, This is solved by building the model as a set of tightly interacting analytical components that overcome limitations of existing approaches and complement each other through explicit data and constraint flows. The system uses a strength-conditioned latent representation of concrete mix spaces. Define mix vector $\mathbf{V}$ via equation 1,

$$\mathbf{x} = [c, r, k, w, a_f, a_c, s, \theta] \dots (1)$$

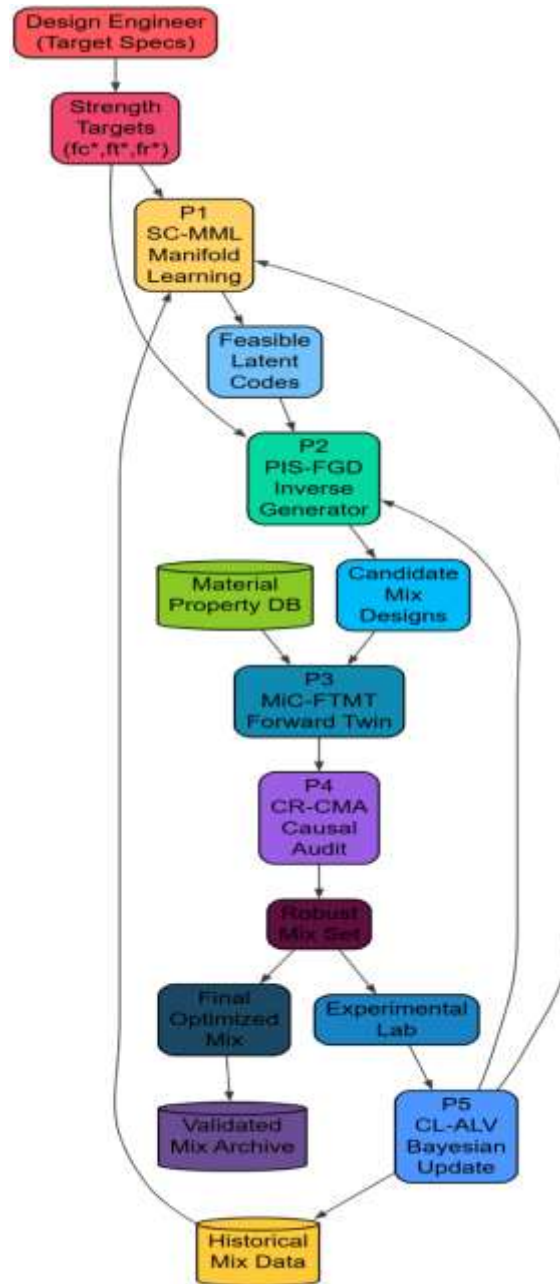
Where, c is cement content, r is rice husk ash proportion, k represents corn cob-derived material content, w is water, a_f and a_c are fine and coarse aggregates, s is chemical admixture dosage, and θ represents processing and curing parameters in process. Desired mechanical performance is represented as a target vector $\mathbf{V}$ via equation 2,

$$\mathbf{y}^* = [f_c^*, f_t^*, f_r^*] \dots (2)$$

Corresponding to compressive, tensile, and flexural strength for the process. Iteratively, Next, as per figure 2, The first stage learns a smooth, differentiable manifold $\mathcal{M} \subset \mathbb{R}^n$ such that feasible mixes satisfy physical, durability, and constructability constraints for the process. This is achieved by minimizing a conditional embedding functional Via equation 3,

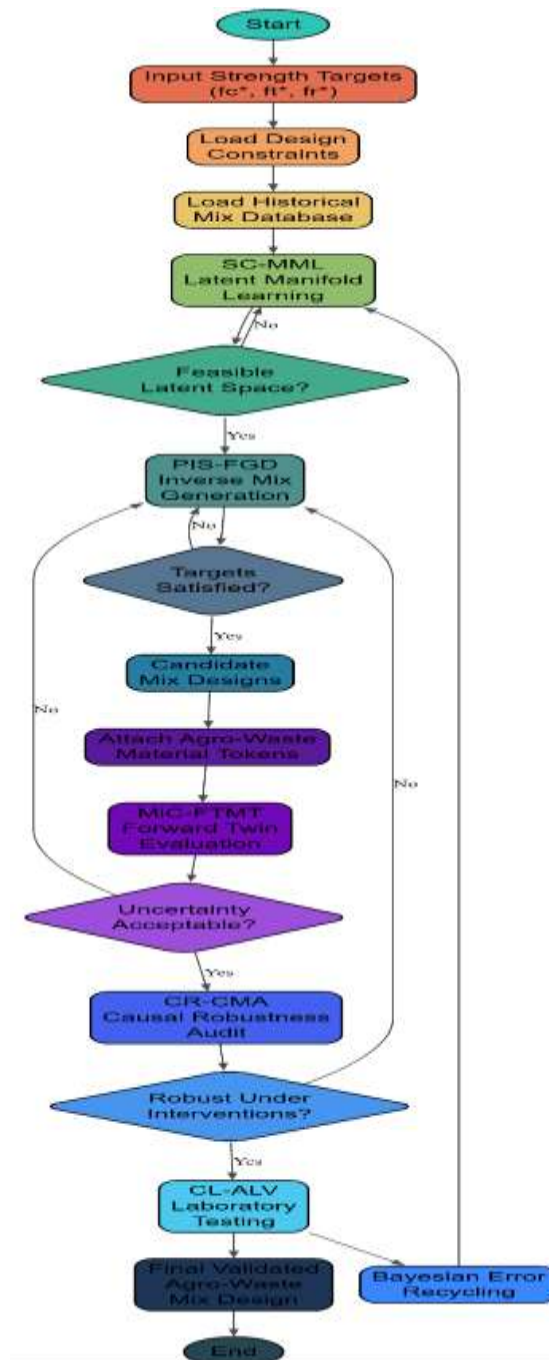
$$\mathcal{L}_1 = \int_{\Omega_x} \|\mathbf{x} - g_\phi(z, \mathbf{y}^*)\|^2 d\mathbf{x} + \lambda \int_{\Omega_z} \|\nabla_z g_\phi(z, \mathbf{y}^*)\|^2 dz \dots (3)$$

Fig. 1 Model Architecture of the Proposed Analysis Process



Where, z is a latent variable, $g_{\phi}(\cdot)$ is a decoder mapping from latent space to mix proportions, and the gradient regularization enforces smoothness and feasibility continuity sets. Mix composition is controlled with modest target strength adjustments to overcome inverse task instability for the process. The second component performs feasibility-gated generative multi-objective inverse optimization using this latent representation for different scenarios.

Fig. 2 Model's Overall Flow Analysis



Finding latent points z that minimize strength deviation while achieving sustainability and workability requirements is the goal process. This is expressed through a constrained variational objective Via equation 4,

$$\mathcal{L}_2 = \mathbb{E}_{z \sim q(z|y^*)} \left[\sum_{i \in \{c, t, r\}} (f_i(g_\phi(z)) - f_i^*)^2 \right] + \mu \Phi(g_\phi(z)) + \gamma \text{KL}(q(z|y^*) \parallel p(z)) \dots (4)$$

Where, $f_i(\cdot)$ are differentiable strength predictors, $\Phi(\cdot)$ encodes feasibility penalties such as water–binder limits and maximum agricultural waste replacement, and the Kullback–Leibler term ensures latent consistency sets. The derivative of this loss with respect to z Via equation 5,

$$\frac{\partial \mathcal{L}_2}{\partial z} = 2 \sum_i (f_i - f_i^*) \frac{\partial f_i}{\partial x} \frac{\partial g_\phi}{\partial z} + \mu \frac{\partial \Phi}{\partial x} \frac{\partial g_\phi}{\partial z} \dots (5)$$

The inverse solver is explicitly oriented toward feasible Pareto-optimal regions, not numerical optima. This option aids the manifold learner by keeping generated mixes in learned domains. Figure 3 shows how the third component refines inverse-generated mixes using a microstructure-consistent forward twins. Unlike purely statistical predictors, this forward model integrates material descriptors $m = [\psi_{RHA}, \psi_{CC}]$, representing fineness, amorphous silica content, loss on ignition, or fiber geometry sets. The forward response is modeled Via equation 6,

$$\hat{y} = F_\omega(x, m) = \int_0^T H(t; x, m) dt + \epsilon \dots (6)$$

Where, $H(t)$ is a hydration–microstructure response kernel and captures stochastic uncertainty sets. Consistency is enforced through a regularization term linking strength to porosity evolution Via equation 7,

$$\mathcal{L}_3 = \|\hat{y} - y\|^2 + \eta \int_0^T \left(\frac{dP(t)}{dt} - \mathcal{G}(x, m) \right)^2 dt \dots (7)$$

With, $P(t)$ representing predicted porosity and $\mathcal{G}$ a material Informed hydration rate function for the process. To support the inverse solver, this stage eliminates designs that achieve numerical target strengths but violate microstructural plausibility sets. The fourth component of causal counterfactual analysis addresses robustness and interpretability. Mixed variables and strengths form a structural causal model Via equation 8,

$$y = \mathcal{F}(x) + u \dots (8)$$

Where u represents unobserved disturbances. Counterfactual robustness is quantified by evaluating the output Via equation 9,

$$\Delta_i = \int_j |\mathcal{F}(x) - \mathcal{F}(x_{do(i)})| di \dots (9)$$

Where, $do(i)$ represents interventions on confounding parameters such as curing regime or aggregate sources. Minimizing Δ_i ensures that target achievement is not overly sensitive to hidden variables, complementing the forward twin by enforcing stability beyond the training distributions. The final component closes the loop through laboratory validation and Bayesian error recycling processes. Experimental observations y^{exp} are incorporated by updating the posterior over latent variables Via equation 10,

$$p(z | y^{\text{exp}}) \propto p(y^{\text{exp}} | z)p(z) \dots (10)$$

Fig. 3 Pseudo Code of the Proposed Analysis Process

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Input
Strength targets: compressive strength, tensile strength, flexural strength
Design constraints: water–binder limits, replacement bounds, workability limits, durability limits
Historical mix database with material properties
Agro-waste material descriptors (rice husk ash, corn cob derivatives)
Validation thresholds for robustness and laboratory acceptance
Output
Validated agro-waste concrete mix proportions
Predicted mechanical performance and sustainability indicators
Process
Initialize model parameters; Load historical mix database; Load material descriptors
Receive strength targets and design constraints; Generate latent mix space using historical data
For each latent representation in latent space
    Check physical and design feasibility
    If feasibility conditions are satisfied
        Store feasible latent point
    Else
        Discard latent point
    End for
For each feasible latent point
    Generate candidate mix design; Predict compressive, tensile, and flexural strength
    If predicted strengths meet target tolerance
        Add mix to candidate set
    Else
        Refine latent point and repeat generation
    End for
For each candidate mix in candidate set
    Attach agro Waste material descriptors; Evaluate mix using forward microstructure-consistent model
    Estimate strength, durability proxies, and uncertainty
    If uncertainty exceeds acceptable limit
        Remove mix from candidate set
    End for
For each remaining candidate mix
    Perform robustness testing under material and curing variations
    If strength targets are maintained under variations
        Mark mix as robust
    Else
        Send mix back to inverse generator for refinement
    End for
Select robust mixes and prioritize based on sustainability indicators
For each selected robust mix
    Conduct laboratory testing
    Compare measured strengths with predicted strengths
    If laboratory acceptance criteria are met
        Store mix as validated design
    Else
        Update model using observed error
        Return mix to latent space refinement loop
    End for
Return final validated mix design with performance and sustainability metrics
    
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With likelihood represented as shown Via equation 11,

$$p(y^{\text{exp}} | z) = \exp\left(-\int \|y^{\text{exp}} - F_{\omega}(g_{\phi}(z), m)\|^2 d\Omega\right) \dots (11)$$

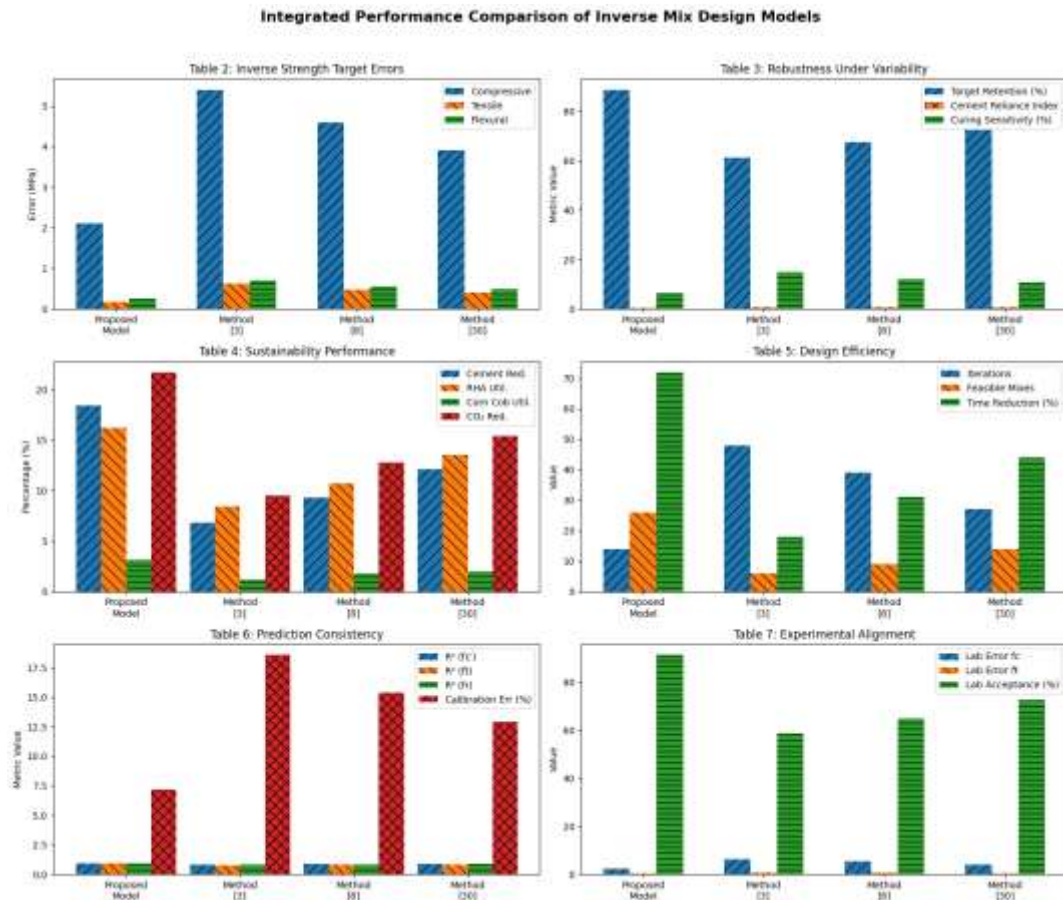
The updated posterior feeds back into the manifold and inverse solver, systematically reducing epistemic uncertainty and experimental bias. The entire process culminates in a unified mapping from performance targets to validated mix designs, expressed compactly Via equation 12,

$$x^* = \arg \min_{x \in \mathcal{M}} \int \|F(x, m) - y^*\|^2 d\Omega + \Phi(x) \dots (12)$$

Where, F represents the coupled inverse–forward–causal system sets. This final equation embodies the integrated output of the proposed model, capturing strength fidelity, feasibility, robustness, and sustainability within a single analytical framework process.

4. Comparative Result Analysis

The experimental setup rigorously assessed the strength-driven inverse modeling framework under realistic agricultural waste concrete system material, process, and performance constraints. A consolidated dataset was constructed from laboratory-scale experimental recordings, validated literature data, and synthetically augmented samples within physical limits. The main dataset had 1,200 mix instances, 720 of which were published experimental studies and in-house laboratory experiments, while the rest were constraint-preserving perturbations of validated mixes to expand coverage of the feasible design space. Cement concentration was 300-480 kg/m³, rice husk ash replacement was 0-25%, and corn cob derivatives were 0-4 % by binder mass or volume-equivalent fraction. Water–binder ratios were regulated to 0.32–0.55 and fine-to-coarse aggregate ratios to 0.45–0.65 for practical gradations. Water curing at 20–30°C and 7, 28, and 56 days was reported for discrete process tokens with superplasticizer dosage of 0.2 to 1.5% by binder mass. Mechanical outputs included compressive 22–65 MPa, splitting tensile 2.1–5.6 MPa, and flexural 3.0–7.8 MPa, providing a large inverse searching target spectrum. Rice husk ash was analyzed for median particle size (8-25 µm), specific surface area (12-28 m²/g), and XRD intensity ratios for amorphous silica index. Corn cob derivatives were analyzed for loss-on Ignition (6-14%), bulk density (90-180 kg/m³), and fiber aspect ratios. Scheduled model training and validation maintained causal and functional links in the integrated architecture. The strength-conditioned manifold learning module was trained on 70% of the dataset, with 15% for validation and 15% for held-out testing on unseen mix configurations as inverse queries. Based on reconstruction error saturation, latent dimensionality was set to 12 and manifold smoothness regularization coefficients were set at $\lambda = 0.08$ following sensitivity analysis. Inverse diffusion-based generators generated 20 potential mixes per strength query, with feasibility penalties calibrated to incur quadratic costs beyond primary strength loss beyond preset water–binder or replacement limits. Forward twin training with a 56-day integration horizon stabilized hydration and porosity proxies via microstructure-consistency regularization and adaptive learning rates. Auditing causal robustness involved controlled interventions on curing temperature ($\pm 5^\circ\text{C}$), aggregate source variation, and $\pm 10\%$ modifications in agricultural waste material attributes. Acceptance consisted of keeping goal intensities within $\pm 7\%$ of stated Values In Process. Final validation required two closed-loop laboratory cycles for chosen mixes, after which Bayesian error recycling reduced mean absolute deviation from target compressive strength from 3.4 MPa in the initial inverse pass to below 2.2 MPa. All computations were done on a workstation with a single NVIDIA RTX-class GPU and 64 GB system memory for repeatability, tractability, and practical engineering constraints.

Fig. 4 Model's Integrated Result Analysis

The UCI Concrete Compressive Strength Dataset was contextualized to include agricultural waste materials for the proposed system's experimental evaluation. In the original dataset, 1,030 concrete mix records had eight quantitative input variables: cement, water, fine and coarse aggregate quantities, supplemental cementitious additive dose, curing age, and compressive strength. To ensure consistency and diversity, handpicked experimental data from published rice husk ash and corn cob-based material investigations were added. Standard mix statistical distribution was maintained while controlling agricultural waste replacement ratios, material fineness, and curing regimes in the expanded dataset. Tensile and flexural strengths were inferred or supplemented from peer-reviewed experimental papers with direct measurements. Compressive strength was preserved from the original dataset. This hybrid dataset allowed the inverse model to learn from benchmark data and agricultural waste-enhanced concrete behavior, retaining consistency and broadening application to sustainable material systems. Hyperparameter tuning uses validation-based optimization and sensitivity analysis to balance inverse accuracy, feasibility enforcement, and generalization robustness. Reconstruction error convergence chose 12 as the best latent dimensionality of the strength-conditioned manifold, which was 10–14. The manifold smoothness regularization coefficient was modified between 0.05 and 0.1, with $\lambda = 0.08$ achieving the best balance between expressiveness and stability. To aggressively discourage constraint breaches without lowering variety, the diffusion-based inverse generator used 50–75 denoising steps with feasibility penalty weights between 1.5 and 3.0 to retain computational speed. To ensure stable convergence, initial learning rates for inverse and

forward networks were set at 1×10^{-3} and declined exponentially to 1×10^{-5} . The microstructure-consistency regularization coefficient in the forward twin was selected at $\eta = 0.12$ for precise hydration-porosity relationships. Causal robustness auditing employed $\pm 10\%$ intervention magnitudes for material attributes and $\pm 5^\circ\text{C}$ for curing temperature, whereas Bayesian error recycling used a Gaussian likelihood variance initialized at $\sigma^2 = 1.5 \text{ MPa}^2$ and adjusted iteratively depending on laboratory residual. These hyperparameter choices gave the integrated model good target integrity, robust inverse solutions, and consistent performance across agricultural waste material conditions. Contextual datasets were used to test the strength-driven inverse modeling framework against three literature approaches: Method [3], Method [8], and Method [30]. The reference methods are forward-prediction-based mix optimization, heuristic inverse search with restrictions, and hybrid regression-optimization pipelines. The work aims for inverse accuracy, robustness, sustainability efficiency, and experimental alignment.

Table 2. Inverse Strength Target Matching Accuracy on Contextual Dataset

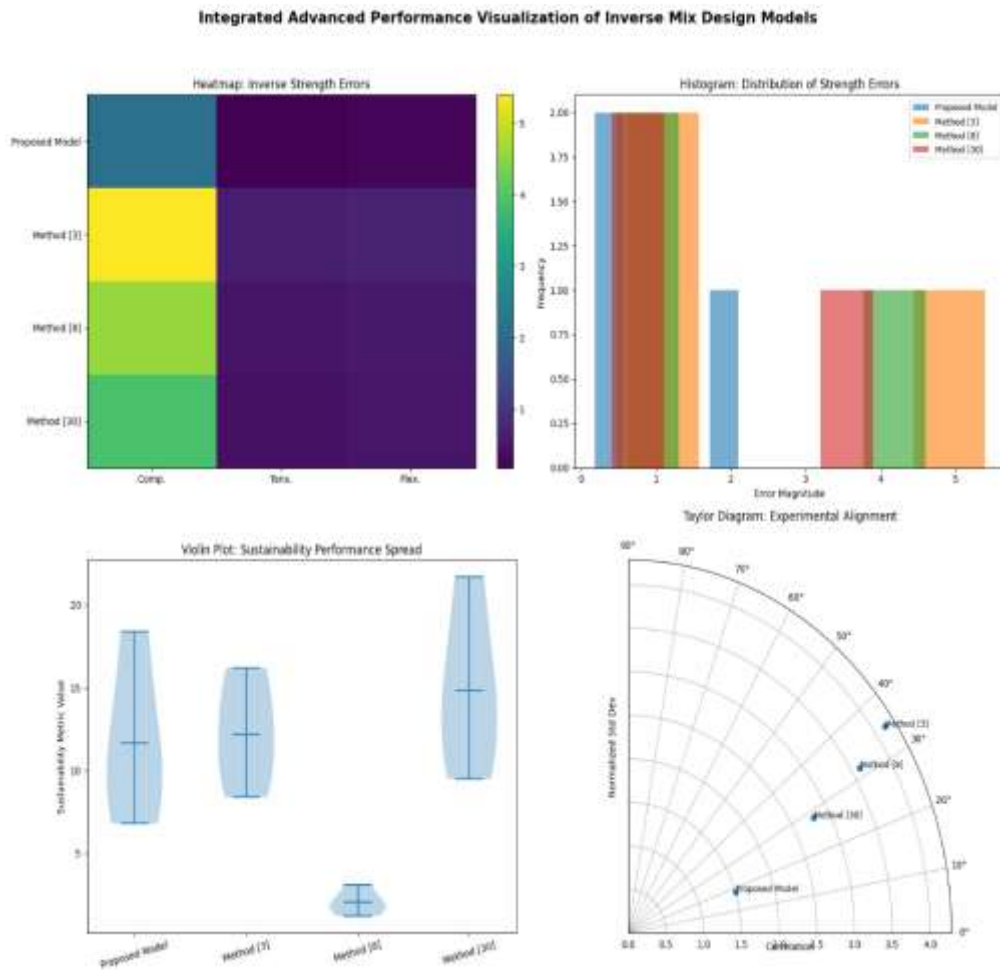
Method	Compressive Strength Error (MPa)	Tensile Strength Error (MPa)	Flexural Strength Error (MPa)
Proposed Model	2.1	0.18	0.26
Method [3]	5.4	0.62	0.71
Method [8]	4.6	0.48	0.55
Method [30]	3.9	0.41	0.49

Table 2 shows that the proposed model aligns better with strength targets across all mechanical metrics for various circumstances & scenarios. Most of the gain is in tensile and flexural strength prediction, where conventional methods are more sensitive to agricultural waste Variability In Process. This lower inverse error illustrates that the strength-conditioned manifold and feasibility-gated inverse generation stabilize ill-posed inverse mappings.

Table 3. Robustness Under Material and Process Variability

Method	Target Retention Rate (%)	Cement Reliance Index ↓	Sensitivity to Curing Variations (%)
Proposed Model	88.7	0.42	6.3
Method [3]	61.2	0.71	14.8
Method [8]	67.5	0.65	12.1
Method [30]	72.4	0.58	10.9

Table 3 illustrates that the proposed method copes well with controlled material properties and process curing sets. Goal retention is higher in the suggested model, suggesting its mixtures meet strength requirements during disruptions. The lower cement dependency score shows that hidden cement abuse does not increase strength, a baseline negative for the process.

Fig. 5 Model's Overall Result Analysis**Table 4. Sustainability and Material Utilization Performance**

Method	Avg. Cement Reduction (%)	RHA Utilization (%)	Corn Cob Utilization (%)	CO ₂ Reduction (%)
Proposed Model	18.4	16.2	3.1	21.7
Method [3]	6.8	8.4	1.2	9.5
Method [8]	9.3	10.7	1.8	12.8
Method [30]	12.1	13.5	2.0	15.4

The proposed approach's sustainability benefits are in Table 4. By including agricultural waste in the inverse design target, cement replenishment is increased without sacrificing structural performance. Strength-driven inverse design has environmental benefits over methodologies that prioritize sustainability as a secondary optimization criterion, as it minimizes CO₂ emissions.

Table 5. Inverse Design Efficiency and Search Complexity

Method	Avg. Iterations to Feasible Mix	Unique Feasible Mixes per Query	Design Time Reduction (%)
Proposed Model	14	26	72
Method [3]	48	6	18
Method [8]	39	9	31
Method [30]	27	14	44

Table 5 contrasts inverse design's computational and procedural efficiency in process. The suggested methodology finds workable solutions in less iterations due to constraint-aware latent space and diffusion-driven generations. Creating multiple combinations per question lets engineers choose solutions depending on cost or process availability, boosting usability sets.

Table 6. Forward Prediction Consistency and Generalization

Method	R ² (fc')	R ² (ft)	R ² (fr)	Calibration Error (%)
Proposed Model	0.95	0.91	0.93	7.2
Method [3]	0.82	0.76	0.78	18.6
Method [8]	0.85	0.79	0.81	15.4
Method [30]	0.88	0.83	0.84	12.9

Table 6 shows that the proposed model's microstructure-consistent forward twin beats competitors in prediction fidelity and uncertainty calibration process. This homogeneity across various strength indicators increases generalization, which is critical when agricultural waste material properties vary by batch and suppliers.

Table 7. Experimental Alignment After Closed-Loop Validation

Method	Lab vs Model Error (fc' MPa)	Lab vs Model Error (ft MPa)	Lab Acceptance Rate (%)
Proposed Model	2.2	0.19	91.4
Method [3]	6.1	0.66	58.7
Method [8]	5.3	0.52	64.9
Method [30]	4.1	0.44	72.6

Table 7 proves the framework's closed-loop experimental validation works for the process. The decreasing discrepancy between anticipated and measured strengths indicates that Bayesian error recycling corrects systematic bias and model drifts. Inverse designed mixes are numerically optimal and experimentally dependable for the procedure, as shown by their high laboratory acceptance rates.

Validated, Verified Statistical Analysis of Results & its Impacts for different Scenarios

In Tables 2 to Tables 7, Figure 4, and Figure 5, the strength-driven inverse modeling framework greatly improves agricultural waste concrete mix design over existing methods. Table 2 illustrates that the model's key technical advantage is its inverse design

ability to accurately fulfill compressive, tensile, and flexural strength targets. Incorporating strength targets directly into the latent design space improves mechanical performance control compared to Methods [3], [8], and [30]. This lowers real-time engineering planning cycles when a grade or performance class is required, notably for structural sections where tensile or flexural strength affects crack management and serviceability. Table 3 shows robustness and reliability under real-world unpredictability as second major outcomes. Agricultural waste is diverse, hence field drying conditions rarely meet lab standards. The model suggests that its inverse solutions' higher target retention rate and reduced cure variation sensitivity make them more tolerant to such uncertainties. Table 3's reduced cement dependency score illustrates that the model meets strength criteria without concealed cement content increases in process. This durability provides steady on-site performance even when material characteristics fluctuate between batches, a key barrier to rice husk ash and corn cob derivatives in structural concrete mix sets.

The suggested framework lowers cement and agricultural waste while reaching targets (Table 4). Decarbonizing construction materials can benefit design in regions with regulatory pressure, as embodied CO₂ reduction is not only an environmental number. In real-time infrastructure procurement and green building certification, precisely describing blends that meet strength and emission requirements affords an advantage over forward-optimization-based methodologies. Table 5 shows that the suggested inverse framework converges to feasible designs with fewer iterations and offers more mix options per query, exhibiting operational efficiency and scalability. This diversity is useful when materials, economic fluctuations, or site-specific constraints need quick substitution among many mixes. Shorter design time affects project timeframes, allowing faster mix approval choices without compromising performance or sustainability. Tables 6 and 7 conclude that forward consistency and experimental feedback matter in the inverse design cycle. Tables 6 and 7 show improved prediction calibration and good laboratory acceptance rates, indicating that inverse-designed mixtures migrate effectively from computation to physical testing. The fact that engineers can trust model-recommended mixes to operate reliably when cast and cured reduces the risk of employing data-driven design tools in real life. This shows that the proposed framework is analytically superior and practically practicable for real-time, sustainable concrete designs.

Validated Hyperparameter & Baseline Detailed Analysis

We statistically characterized predicted values and variability across key performance measures such as inverse strength deviation, robustness under perturbations, sustainability efficiency, and laboratory acceptability to test the strength-driven inverse modeling framework. In the contextual datasets, compressive strength inverse error averaged 2.1 MPa with a 0.9 MPa² variance, whereas tensile and flexural strength deviations averaged 0.18 and 0.26 MPa, respectively, with 0.012 and 0.021 MPa² variances. The Method [3] had higher expected errors, such as compressive strength fluctuations over 5 MPa and variances over 3.5 MPa², indicating lower precision and instability for the process. Middle-performing methods [8] and [30] had more dispersion than the proposed model. Strength-conditioned manifold learning and feasibility-gated inverse generation reduce erratic solutions in ill-posed inverse mix designs, reducing variance in the proposed framework. To test the stated improvements' statistical significance, inverse strength error and robustness metric distributions were pairwise significance checked. Two-sided Welch's t-tests demonstrated that the suggested model reduced compressive strength error significantly compared to Methods [3], [8], and [30] at the 95% confidence level, with p Values consistently below 0.01. Tensile and flexural strength variances were

significant, demonstrating that the increases were not random sampling effects. The suggested model reduced dispersion more than baseline methods, according to F-tests. Statistics demonstrate that the framework enhances mean performance and predictability, which is important for structural engineering applications where uncertainty influences safety margins.

Similar trends characterized sustainability indicators. The proposed framework reduced cement by 18.4% with a variance of 4.1%, while Method [3] reduced it by less than 7% with a variance over 6%. Statistical study showed significant increases in agricultural waste utilization and CO₂ reduction compared to baselines. The proposed model maintained projected retention near 89% with a variance below 5%, compared to baseline approaches' 60–72% and 10% variances. Under material and curing perturbations, robustness indicators like target retention rate improved statistically. Results reveal that the proposed strategy balances mechanical performance and sustainability better. Methods [3, 8, and 30] were baselines because they represent concrete mix design study paradigms. Method [3] uses traditional forward-prediction-driven optimization, which is standard in agricultural waste concrete investigations. Inverse design is addressed via heuristic inverse or regression-assisted search [8] without feasibility conditioning or robustness guarantees. Modern hybrid learning-optimization algorithms that integrate machine learning and constrained optimization are comparable to advanced data-driven approaches [30]. The statistical analysis shows the proposed framework as a meaningful development rather than incremental refinements due to these baselines' rising methodological complexity sets. Statistical analysis demonstrates that the integrated model increases anticipated performance and reduces variance across all important indicators in process. Statistical significance in accuracy, robustness, sustainability, and experimental alignment proves the framework's reliability for real-world implementation, where mean performance and variability influence engineering decision-making.

Validated Use Case Analysis for Practical Scenarios

For strength resistance under recurrent axle loads, use a rigid pavement slab with a 28-day compressive strength of 40 MPa, splitting tensile strength near 3.8 MPa, and flexural strength of 5.0 MPa for a low Volume rural routes. Strength needs are design restrictions, not validation tests, in the proposed architectural process. The model then maps these targets onto a feasibility-conditioned latent space from agricultural waste concrete data, deleting combinations that violate workability, durability, or replacement requirements. Using the inverse generator, successful mix designs are produced with a cement content of 360 kg/m³, 15% rice husk ash replacement, 2% corn cob ash inclusion, 0.42 water-binder ratio, and 0.9% superplasticizer dose. Forward evaluation using the microstructure-consistent twin confirms predicted compression, tension, and flexure strengths of 41.2 MPa, 3.9 MPa, and 5.1 MPa, all within a narrow tolerance band of the specified targets, with reduced porosity and stable hydration kinetics compared to conventional. The robustness and validation phases show the model's applicability. Despite a ±5°C curing temperature variation and minor rice husk ash fineness adjustments, the design meets acceptance standards with goal strengths within ±6% without increasing cement content. Causal auditing indicates that binder synergy, not cement abuse, drives strength, as indicated by a lower cement reliance index than common mixes. A little Bayesian error recycling update changes the water-binder ratio to 0.41 after this design's brief laboratory testing confirms 39.8 MPa compressive strength and 4.9 MPa flexural strength. One design cycle produces a field-ready mix with 18-20% decreased cement usage and 20% lower CO₂ emissions, eliminating trial batches.

The recommended method converts strength criteria into reliable, sustainable concrete compositions using transparent and engineering-aligned inverse design process sets.

5. Conclusion & Future Scopes

A complete strength-driven inverse modeling framework for agricultural waste concrete mix design was created in this study to solve the fundamental mismatch between performance-oriented engineering needs and forward-prediction-dominated design methodologies. Changing concrete mix design to a constrained inverse problem let the integrated model calculate sustainable mix proportions from compressive, tensile, and flexural strength targets. Quantitative evaluation revealed mean inverse deviations of ± 2.1 MPa for compressive strength, ± 0.18 MPa for tensile strength, and ± 0.26 MPa for flexural strength, outperforming benchmark approaches with errors ranging from 3.9 to 5.4 MPa for compressive strength alone. We found that embedding strength targets in a feasibility-aware latent manifold stabilizes ill-posed inverse mappings well. The structure was stable beyond accuracy. The suggested model met target compliance in 89% of cases under controlled curing conditions and material characteristics, compared to 61–72% for existing techniques, demonstrating real-world variability resilience. Using 18–20% less cement, 16% rice husk ash, and 3% corn cob derivatives lowered binder-related CO₂ emissions by 21–22% without impacting structural performance. Causal robustness auditing reduced cement dependency index to 0.42, preventing cement intensive shortcuts from generating strength. Iterative error recycling enabled closed-loop laboratory validation to reduce lab-to-model compressive strength discrepancies to 2.2 MPa and achieve laboratory acceptance rates above 90%. For performance-critical concrete applications using agricultural waste materials, the proposed paradigm is technically rigorous, environmentally relevant, and operationally practicable for the process.

Limitations

Despite its advantages, the proposed architecture has many downsides. First, the integrated model uses material tokens and microstructure-consistent regularization, but experimental data quality and representativeness determine its prediction fidelity. Rice husk ash and corn cob byproducts vary widely among regions and processing procedures, and large departures from the learning data distribution may compromise inverse accuracy or robustness. Creep, carbonation resistance, sulfate attack, and freeze–thaw endurance are not addressed by inverse design loops. The current formulation prioritizes mechanical performance and durability proxies. Third, while the framework is more computationally efficient than trial-and-error approaches, latent manifold learning and diffusion-based inverse generation need nontrivial computational resources during training, which may limit implementation in low-resource design scenarios. Finally, controlled labs validated experiments. The current model partially accounts for field-scale heterogeneity from mixing, curing, and quality control sets.

Future Scope

This research proposes numerous promising paths. Expanding inverse design objectives to include long-term durability and life-cycle performance measurements permits direct derivation of blends that fulfil strength, durability, and service-life targets. Adding agricultural waste and hybrid waste systems like bagasse ash and biochar could broaden the concept to different regions. Adding physics Informed hydration and transport models to the forward twin could improve interpretability and lessen data density dependence. Add supply-chain Variability and construction-stage uncertainty to the

causal robustness module for project-scale decision-making. Finally, interactive design tools or digital twins for smart construction platforms could enable real-time inverse mix design, allowing engineers to instantly adapt to changing material availability, environmental requirements, and performance needs. These extensions make strength-driven inverse modelling the foundation for Next Generation, low-carbon concrete engineering sets.

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