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A Model to Predict the Strength of Highway Culvert made from Cinchona industrial Waste and Pulverized Plastic as Partial Replacement of Cement and Sand in Concrete

Omach Antony Owuonda[1*], Fundi Isaac Sanewu[2], Nyongesa Daniel Wekesa[3]

Department of Civil, Construction and Environmental Engineering,

Jomo Kenyatta University of Agriculture and Technology, Nairobi, Kenya

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Abstract: **The increasing demand for sustainable and high-performance concrete necessitates accurate prediction of its mechanical and durability properties. This study developed Artificial Neural Network (ANN) models to estimate compressive, flexural, and tensile strength, as well as setting times and workability parameters, based on inputs of pulverized plastic waste (PPW) and cinchona industrial ash (Ci). The model was trained and validated using experimental datasets. Evaluation metrics such as RMSE, MAE, R^2, and scatter index confirmed excellent model performance, especially for strength-related outputs ($R^2 \approx 0.99$). These results were consistent with related ANN applications in literature, reinforcing its predictive robustness. The proposed model can aid in optimizing concrete mixes using industrial waste, contributing to circular economy and sustainable infrastructure. Further application in field-scale design is recommended.**

Keywords: **ANN; Cinchona Industrial Waste (Ci); Mathematical Model; Pulverized Plastic Waste (PPW).**

I. INTRODUCTION

The construction industry is one of the largest consumers of natural resources and contributors to environmental degradation. Conventional concrete production alone accounts for approximately 8% of global CO_2 emissions due to the energy-intensive manufacturing of cement [1]. The world generates over 300 million tons of plastic waste annually, with more than 80% of it ending up in landfills or the natural environment [2, 3]. Developing countries, including Kenya, face a growing challenge of managing both industrial waste and non-biodegradable plastic materials. Similarly, industrial processes such as cinchona bark extraction generate vast amounts of alkaline ash byproducts, often disposed of without further utilization.

In highway infrastructure, culverts are critical components that must maintain long-term mechanical integrity under traffic loads and environmental exposure [4, 5]. Traditional concrete used in culverts relies heavily on virgin sand and cement, contributing to natural resource depletion and high carbon footprints. The high cost and environmental impact of cement and sand extraction call for alternative sustainable materials that can match or exceed performance requirements.

This study proposes the use of Cinchona Industrial Waste (Ci) as a partial replacement for cement and Pulverized Plastic Waste (PPW) as a partial substitute for sand in the production of concrete culverts. However, the incorporation of these non-traditional materials introduces uncertainty in mix performance due to complex interactions and variable chemical compositions. Predicting the resulting strength and durability properties becomes a critical challenge. To address this, the objective is to develop a robust predictive model based on artificial neural networks (ANNs) capable of estimating key

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mechanical and workability properties of modified concrete mixes. These include compressive strength, flexural strength, tensile strength, water absorption, initial and final setting times, and slump. The ANN model is trained on experimentally obtained data reflecting a wide range of mix proportions and performance outcomes, allowing it to capture nonlinear dependencies that traditional analytical models cannot. The significance of this objective lies in enabling data-driven, performance-based mix design. With an accurate model, engineers can reverse-engineer desired concrete properties to find the most effective blend of Ci and PPW. This not only supports the sustainable use of industrial and plastic waste but also reduces the reliance on virgin materials and promotes circular economy principles in construction.

This study responds to urgent global and local environmental challenges by proposing a scientifically grounded, technologically advanced method for optimizing concrete mix designs using waste materials. The predictive model developed serves as a practical tool for implementing green construction practices in highway culvert development, thus contributing to both infrastructure resilience and ecological sustainability.

II. RELATED WORKS

A. Empirical Review

The prediction of concrete strength has remained a vital concern in civil engineering and material science, especially given the industry's increasing shift towards sustainability, resource efficiency, and performance optimization. Traditional empirical approaches, though useful, often lack the adaptability and precision needed for complex modern concrete mixes incorporating supplementary cementitious materials or waste products [6, 7, 8, 9]. As a result, mathematical modeling techniques, including both classical statistical methods and advanced soft computing approaches, have gained traction for predicting key performance parameters such as compressive strength, tensile strength, and flexural capacity. These models utilize input parameters such as mix proportions, curing times, and physical properties of materials to simulate and forecast the behavior of hardened concrete under different conditions.

To predict the mechanical performance, specifically, compressive strength, of such modified concrete mixes, [10] study proposes and compares several mathematical modeling techniques. Linear Regression (LR), Non-Linear Regression (NLR), and Artificial Neural Networks (ANN) were applied to model the relationship between material composition and compressive strength. The ANN approach, leveraging its capability to learn complex, nonlinear patterns, demonstrated superior predictive accuracy relative to the statistical models. Quantitative evaluation revealed that the ANN model achieved a significantly lower scatter index ($SI < 0.1$) and exhibited a coefficient of determination (R^2) that was 22% higher than that of LR and 17% higher than NLR. The findings underscore the potential of ANN as a reliable tool for optimizing pervious concrete design with waste materials, offering a viable pathway toward sustainable construction practices and effective flood mitigation in climate-vulnerable regions.

[11] study proposed the application of a soft-computing approach, specifically the Gene Expression Programming (GEP) technique, to develop a robust predictive model. The model was trained on a comprehensive dataset comprising four key input variables: the contents of RHA, CWP, GWP, and the curing period (CD). A data split strategy was adopted, where 70% of the dataset was allocated for training, 15% for testing, and the remaining 15% for external validation using experimental results. The predictive model's performance was evaluated through multiple statistical indicators and was benchmarked against conventional regression models and sensitivity analysis. The GEP model yielded strong correlation coefficients (R-values) of 0.95, 0.93, and 0.89 for training, testing, and validation phases, respectively, along with a low objective function (OF) value of 0.04. These results indicated a high level of accuracy and generalization. The study derived a closed-form mathematical expression from the optimal GEP model, enabling practical estimation of compressive strength for concrete mixes incorporating ternary pozzolanic blends. The model demonstrated strong adaptability and predictive reliability.

[9] study proposed the use of backpropagation-based artificial neural networks (ANN) to model and predict compressive strength. A feedforward multilayer perceptron architecture was trained using 1,030 data sets involving various concrete mix designs. Input parameters included cement, water, aggregates, admixtures, and age. The ANN achieved high prediction accuracy with an average error of less than 5 MPa. The best performance was obtained when using a three-layer architecture and Levenberg-Marquardt optimization. Neural networks demonstrated superior predictive ability for concrete strength compared to linear regression, confirming their suitability for complex material systems.

[12] study proposed correlating non-destructive pulse velocity and maturity methods to predict in-situ concrete strength development. Cylindrical specimens were monitored for pulse velocity and temperature-time history. Results were fitted to regression models. A reliable correlation was established between maturity index and compressive strength. Pulse velocity showed strong linearity with strength after early hydration stages. Both methods offered potential for early-age strength prediction, enabling better scheduling of formwork removal and load application.

[8] study suggested using regression models to estimate strength based on water-cement ratio and curing temperature. Concrete samples with varying silica fume content were cured under different conditions. Regression curves were fitted using experimental strength data. Compressive strength showed a strong inverse correlation with water-binder ratio. Regression models provided reliable estimates with acceptable standard deviations. The study validated the use of regression models for strength prediction in HPC, aiding mix design optimization.

[7] study investigated the potential of ultrasonic pulse velocity (UPV) for rapid, non-destructive strength estimation. Cylindrical specimens were tested for UPV and compressive strength over time. Regression analysis linked the two parameters. A logarithmic relationship was established between UPV and compressive strength, with good agreement after 7 days of curing. UPV was shown to be a practical tool for estimating early-age strength, particularly useful in field applications.

[13] study used genetic programming (GP) to derive an explicit predictive model for compressive strength. A database of 500 concrete mixes was used to evolve GP models. Inputs included mix components and curing age. The GP model yielded a closed-form equation with a correlation coefficient of 0.94. It performed better than traditional regression. Genetic programming provided an interpretable and accurate tool for modeling concrete strength and simplifying design tasks.

[14] study developed ANN models to predict compressive strength of concrete incorporating fly ash and silica fume. ANN models were trained using input parameters such as cement, admixtures, age, and water-binder ratio. A total of 384 samples were used. ANN showed excellent accuracy with R^2 values above 0.96 and RMSE below 3 MPa. It outperformed regression-based counterparts. ANN was confirmed as a powerful tool for modeling high-performance concrete, allowing better prediction and control of strength development.

[15] proposed using cinchona ash to replace cement partially and assessed the feasibility of incorporating this waste product into compressed concrete blocks and structural wall panels. The chemical composition of cinchona ash was compared with ordinary Portland cement (OPC) and pozzolanic cement to evaluate compatibility and reactivity. The methodology involved replacing cement with cinchona ash in increments from 0% to 100% at 20% intervals. Two grades of cement, C32.5 and C42.5 from two manufacturers, were examined. Concrete blocks of dimensions 140 mm $\times$ 160 mm $\times$ 290 mm were molded at a compaction pressure of 0.015 N/mm ^{2} using cement-to-sand ratios ranging from 1:2 to 1:8. Physical and mechanical tests were conducted after curing. Furthermore, structural wall panels (1.20 m $\times$ 0.14 m $\times$ 1.00 m) made from cinchona-based blocks and traditional machine-cut stones were subjected to strength evaluations. The study found that water demand for standard consistency increased with ash content, peaking at 111% for pure cinchona ash compared to 36–39% for OPC and pozzolanic cements. Partial replacement of 20% cement with ash decreased the initial setting time to between 10 and 24 minutes. Among the cements, C42.5 from Company B recorded the shortest initial setting time (3 hours), while pure ash exhibited the longest (approximately 7 hours and 30 minutes). Final setting time initially decreased with ash replacement but later increased beyond a certain threshold. Specific gravity of the ash-blended cement decreased as ash content increased. The ultrasonic pulse velocity of blocks made with cinchona ash and Ndarugu stones ranged from 1.34 to 1.84 km/s. Wall panels constructed from cinchona ash-based blocks showed superior compressive strength and elastic modulus compared to those built with Ndarugu machine-cut stones. The research demonstrated that cinchona industrial waste ash could effectively be used as a partial cement replacement in the production of concrete blocks. Load-bearing blocks were achievable with up to 70% ash content for specific cements, while non-load-bearing blocks were viable with ash replacement levels between 70% and 85%.

B. Summary of Literature

The reviewed studies collectively demonstrate the growing application of statistical and AI models, such as LR, NLR, ANN, GEP, and GP, in predicting the compressive strength of concrete. ANN consistently emerged as the most accurate tool, achieving higher coefficients of determination (e.g., R2>0.96R^2 > 0.96R2>0.96) and lower errors compared to traditional regression methods [10,9,14]. Several works also explored correlations between non-destructive tests, such as ultrasonic

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pulse velocity, and compressive strength, confirming strong predictive potential for early-age monitoring [12,7]. Additionally, studies on ternary blends and industrial waste such as RHA, ceramic waste powder (CWP), and glass waste powder (GWP) confirmed the viability of such materials in enhancing mechanical performance [11,15]. Across studies, the focus remained largely on compressive strength, neglecting other key properties such as flexural and tensile strength, water absorption, and durability, critical for applications like culvert construction [10,11,14,15]. Waste material exploration was often limited to single-source industrial byproducts, with minimal consideration for blended waste systems incorporating plastics or biomass ash [10,9,14]. Furthermore, few studies developed performance indices tailored to specific infrastructure needs, and most excluded long-term property evaluation or culvert-specific modeling frameworks [10,11,13,15], emphasizing the need for more comprehensive, application-driven research.

III. METHODOLOGY

A. Summary of Laboratory Experiments

This study adopted an experimental research design involving laboratory testing of concrete incorporating Ci as a partial replacement of cement and PPW as a partial replacement of sand. Multiple concrete mixes were prepared with varying percentages of Ci and PPW and subjected to mechanical and durability tests to determine their suitability for highway culvert construction. The primary goal was to identify the optimum replacement levels that yield acceptable strength and durability characteristics.

a) Materials

The mix comprised Ci ash, PPW, river sand, and ballast chips. Sand and ballast were sourced from vendors along Kangundo Road, Nairobi. The sand used was clean river sand, while the coarse aggregate (ballast) consisted of chips of size 1 inch. Ci ash was obtained from EPZ and used as a partial cement replacement. PPW was collected from Nairobi's Industrial Area and used as partial replacement for sand.

B. Material Batching

Following British Standards such as BS 5400 and BS 8500, a nominal mix ratio of 1:1:2 (cement:sand:ballast) was adopted. The concrete was designed to achieve a target compressive strength of 25 MPa, suitable for culverts exposed to highway loadings. Workability of slump test was performed per BS 812: Part 1:1975 to evaluate particle gradation as shown in Fig. 1.

Fig. 1. From left to right is Slump test setup; Initial casting procedure; casting for tensile strength; compressive test setup; tensile strength test setup; and samples concrete specimen

Fig. 1 shows the workability assessment using the slump cone test, conducted in accordance with BS EN 12350-2:2009. The procedure evaluates the consistency and flow characteristics of freshly mixed concrete. It is essential in determining whether the inclusion of PPW adversely affects the mix's ease of placement. The moderate slump observed suggests a balance between flowability and cohesion, indicating acceptable workability for culvert casting. The figure also show the pouring of fresh concrete into cylindrical molds for the tensile strength test and prismatic molds for the flexural strength test, respectively. The tensile strength test setup follows the guidelines of BS EN 12390-6:2009, which specifies procedures for splitting tensile strength determination of hardened concrete. The flexural strength test setup in figure involves third-point loading of beam specimens, following the provisions of BS EN 12390-5:2009. This test assesses the concrete's resistance to bending stresses and is particularly relevant for culvert slabs that may span short distances. Since the use of Ci and PPW is expected to slightly alter the flexural behavior of the concrete, this evaluation becomes critical for structural application. Figure also presents a collection of cured concrete blocks, stored appropriately for mechanical testing after hydration. Proper curing, per BS EN 12390-2:2019, ensures the validity and reliability of all subsequent strength evaluations. The experimental setup was performed in three phases: The first phase was preliminary test, which was used to estimated the optimal design mix. The second phase was determination of the design mix. The third phases was determination of optimal mix design from the second phase. In this paper, the focus is the use of optimal design mix to estimate the new accurate optimal design mix to remove the element of trial and error during the experiment.

C. Mathematical Formulation and Network Architecture

a) Data Normalization

To ensure consistency and enhance the training efficiency of the neural network models, all input and output data were normalized using z-score standardization. Let $\mathbf{X} \in \mathbb{R}^{n\times d}$ represent the raw input matrix, where n is the number of samples and $d = 7$ corresponds to the number of features—namely, compressive strength, flexural strength, tensile strength, water absorption, initial setting time, final setting time, and slump. Each feature X_j was normalized individually across all samples using the transformation:

$$\tilde{X} * ij = \frac{X*ij-\mu_j}{\sigma_j} \tag{1}$$

where μ_j and σ_j denote the mean and standard deviation of the j^{th} feature, respectively, and $\tilde{X} * ij$ is the standardized value of the i^{th} sample for the j^{th} feature. This normalization process was applied to both the inverse modeling inputs, denoted as $\tilde{\mathrm{X}} * \mathrm{inv}$, and their corresponding targets for PPW and Ci, denoted $\tilde{\mathrm{Y}} * \mathrm{PPW}$ and $\tilde{\mathrm{Y}} * \mathrm{Ci}$. Likewise, the forward modeling inputs—comprising the pair $\widetilde{\mathrm{PPW}}$ and $\tilde{\mathrm{Ci}}$ were normalized to form $\tilde{\mathrm{X}} * \mathrm{fwd}$, and all output property data (the seven strength and workability metrics) were normalized into $\tilde{\mathrm{Y}} * \mathrm{fwd} \in \mathbb{R}^{n\times 7}$. This standardization ensures that all input features contribute equally to the model's learning process and mitigates issues arising from feature-scale imbalance.

b) Neural Network Mapping (Inverse and Forward)

Each target variable, such as PPW, Ci, and the various strength and workability properties—is modeled using a regression neural network. These networks employ a feedforward architecture with two hidden layers and nonlinear activation functions. Let $f_\theta(x)$ represent the function learned by the network, where x is the normalized input vector and θ denotes the set of network parameters (weights and biases). The mapping performed by the neural network can be expressed mathematically as:

$$f_\theta(x) = W_2\phi(W_1x + b_1) + b_2 \tag{2}$$

whereW_1 and W_2 are the weight matrices for the first and second layers, respectively, while b_1 and b_2 are the corresponding bias vectors. The function $\phi(\cdot)$ represents the activation function applied element-wise; in this work, the rectified linear unit (ReLU) was selected due to its non-saturating and computationally efficient nature.

Separate models were trained for each of the output variables. Specifically, the inverse models predict the normalized values of PPW and Ci from the normalized mechanical and workability properties using $f_{\mathrm{PPW}}(\tilde{\mathrm{X}} * \mathrm{inv})$ and $f * \mathrm{Ci}(\tilde{\mathrm{X}}_{\mathrm{inv}})$, respectively. Conversely, for each of the seven performance metrics, a dedicated forward model $f_i(\cdot)$ was trained to map from the normalized PPW and Ci values to the normalized property values. This relationship is expressed as:

$$\tilde{y} * \mathrm{PPW} = f * \mathrm{PPW}(\tilde{\mathrm{X}} * \mathrm{inv}) \tag{3}$$

$$\tilde{y} * \mathrm{Ci} = f_{\mathrm{Ci}}(\tilde{\mathrm{X}} * \mathrm{inv}) \tag{4}$$

$$\tilde{y} * i = f_i(\tilde{\mathrm{X}}_{\mathrm{fwd}}), \quad i = 1, \dots, 7 \tag{5}$$

This modular architecture ensures flexibility and interpretability in predicting both mix design parameters and performance characteristics.

c) Denormalization of Predictions

Following the training and inference processes, all predicted outputs, whether mix design ratios or performance metrics, are initially obtained in their standardized (normalized) form. To interpret these predictions in the original engineering context, it is essential to transform them back to their real-world scales. This is accomplished through denormalization using the inverse of the z-score transformation:

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$$y_j = \tilde{y}_j \cdot \sigma_j + \mu_j \quad (6)$$

In this equation, $\tilde{y}_j$ is the normalized prediction, while μ_j and σ_j are the mean and standard deviation, respectively, used during the original standardization of the j^{th} variable. This denormalization procedure is applied to all model outputs, including the predicted values of PPW and Ci obtained from the inverse models, as well as the seven mechanical and workability properties produced by the forward models. This transformation ensures that all reported results are consistent with the physical units and practical ranges of the input dataset.

d) Prediction Pipeline

Once the neural networks have been trained, the model can be used to infer the optimal mix design ratios (PPW and Ci) for a given set of desired concrete performance characteristics. Let $\mathbf{x}_{\text{target}} \in \mathbb{R}^7$ denote a vector containing the target values for compressive strength, flexural strength, tensile strength, water absorption, initial setting time, final setting time, and slump. The prediction pipeline proceeds as follows. First, the target vector is normalized using the same statistics (mean and standard deviation) computed during training:

$$\tilde{\mathbf{x}} = \frac{\mathbf{x}_{\text{target}} - \mu}{\sigma} \quad (7)$$

The resulting normalized target vector $\tilde{\mathbf{x}}$ is then passed through the inverse neural network models to estimate the corresponding normalized mix design ratios:

$$\widetilde{\text{PPW}} = f_{\text{PPW}}(\tilde{\mathbf{x}}), \quad \tilde{\text{Ci}} = f_{\text{Ci}}(\tilde{\mathbf{x}})$$

These values are subsequently denormalized to yield the actual predicted percentages of pulverized plastic waste (PPW) and cinchona industrial waste ash (Ci):

$$\text{PPW} = \widetilde{\text{PPW}} \cdot \sigma_{\text{PPW}} + \mu_{\text{PPW}}, \quad \text{Ci} = \tilde{\text{Ci}} \cdot \sigma_{\text{Ci}} + \mu_{\text{Ci}}$$

To predict the resulting material properties, these PPW and Ci values are normalized using the forward model's normalization parameters. The normalized pair is then passed through each of the seven trained forward models, each corresponding to one of the target properties. The outputs are again denormalized to recover their physical values. As an optional final step, the predicted properties can be clamped to ensure they do not exceed the specified targets, which may be useful in certain design-constrained scenarios.

D. Network Architecture Diagram

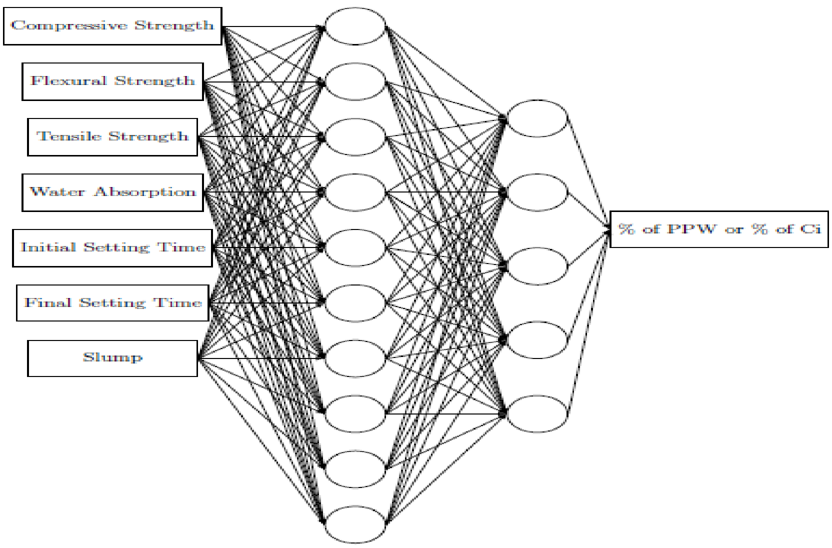

Fig. 2: Neural network architecture used for inverse modeling: mapping target performance properties to optimal PPW or Ci percentages. The same architecture is used for each forward model with PPW and Ci as inputs and properties as outputs.

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The neural network architecture developed in this study supports two primary computational tasks critical to the data-driven design of sustainable concrete: inverse modeling and forward modeling. The inverse model estimates the optimal mix proportions of Pulverized Plastic Waste (PPW) and Cinchona Industrial Waste Ash (Ci) based on target performance criteria. The forward models, conversely, predict key mechanical and workability properties from specified PPW and Ci ratios. The network receives seven input features representing desired concrete performance metrics: compressive strength, flexural strength, tensile strength, water absorption, initial setting time, final setting time, and slump. The forward modeling architecture uses only two inputs: the mix design parameters, PPW and Ci percentages, serving as predictors for the output properties. Both model types share a unified architecture consisting of two fully connected hidden layers. The first hidden layer includes 10 neurons using the Rectified Linear Unit (ReLU) activation function. This offers several advantages: ReLU introduces nonlinearity essential for learning complex relationships, has computational efficiency due to its simplicity, and avoids the vanishing gradient problem prevalent in sigmoid or tanh activations. The second hidden layer contains 5 ReLU-activated neurons, which strike a balance between model capacity and overfitting prevention by reducing the dimensionality of the learned feature space before reaching the output. The output layer comprises a single neuron with a linear activation function. This is ideal for continuous regression tasks where the model must predict scalar quantities such as the amount of PPW or compressive strength. In the inverse modeling phase, the output is either PPW or Ci, each modeled with a separate network. In the forward modeling phase, the same architecture is replicated across seven networks, one for each property to be predicted.

Training is conducted using MATLAB's fitrnet function. Inputs and outputs are standardized via z-score normalization to improve convergence and ensure consistent weight updates. To mitigate overfitting and improve generalization, L_2 regularization with a penalty term $\lambda = 0.01$ is applied. This penalizes excessively large weights that might otherwise adapt too closely to training noise. The models are trained over a maximum of 1000 iterations using a built-in optimization algorithm (e.g., L-BFGS), and internal validation is leveraged for monitoring convergence and applying early stopping if necessary. The mean squared error (MSE) loss function is employed, which is well-suited for regression and emphasizes large deviations.

Each architectural and hyperparameter decision is rooted in a trade-off between model expressiveness and interpretability. The use of ReLU ensures that the model can capture nonlinearities inherent in material-property relationships without introducing training instability. The compact two-layer structure ensures fast training while maintaining sufficient complexity for accurate modeling. The modularity of the architecture allows it to be easily scaled for additional outputs or modified for new input types (e.g., curing conditions, additives).

The researcher can specify the desired property profile of a concrete mix, and the inverse models will return candidate PPW and Ci values. These can then be passed through the forward models to simulate expected outcomes, providing a closed-loop predictive framework. This method enhances design flexibility, accelerates material discovery, and supports sustainable practices by facilitating the optimal reuse of industrial and plastic waste in concrete.

E. Grid Evaluation

To evaluate the behavior of the forward predictive models across a range of mix compositions, a grid-based evaluation approach was implemented. Specifically, discrete sets of values for PPW and Ci were defined over their respective observed ranges. Let these ranges be denoted as:

$$\mathrm{PPW} \in \min(\mathrm{PPW}), \max(\mathrm{PPW})], \quad \mathrm{Ci} \in \min(\mathrm{Ci}), \max(\mathrm{Ci})] \tag{8}$$

Using these intervals, a Cartesian product was constructed to form a comprehensive evaluation set, consisting of all possible combinations of PPW and Ci within the specified bounds. Each pair from this grid was first normalized using the same statistics used during model training, and then passed individually through the seven trained forward models. Each forward model $f_i(\cdot)$, where $i = 1, \dots, 7$, corresponds to a specific concrete performance indicator (e.g., compressive strength, slump, etc.). For a given combination of PPW and Ci, the output vector of predicted properties is defined as:

$$\mathbf{Y}_{\text{pred}} = f_1(\mathrm{PPW}, \mathrm{Ci}), f_2(\mathrm{PPW}, \mathrm{Ci}), \dots, f_7(\mathrm{PPW}, \mathrm{Ci})] \tag{9}$$

This matrix of predictions serves as a valuable tool for conducting mix-design feasibility analysis. It allows practitioners to explore how variations in PPW and Ci affect each concrete property, facilitating the selection of optimal or practical mix ratios under performance constraints. The full grid is exported as a structured dataset for further examination or integration into decision-support systems.

F. Training

The primary goal was to minimize prediction errors and provide a robust estimation framework for material optimization in highway culvert applications. The training and validation loss curves is presented in Fig. 3 provide insights into the models' convergence behavior and generalization capabilities.

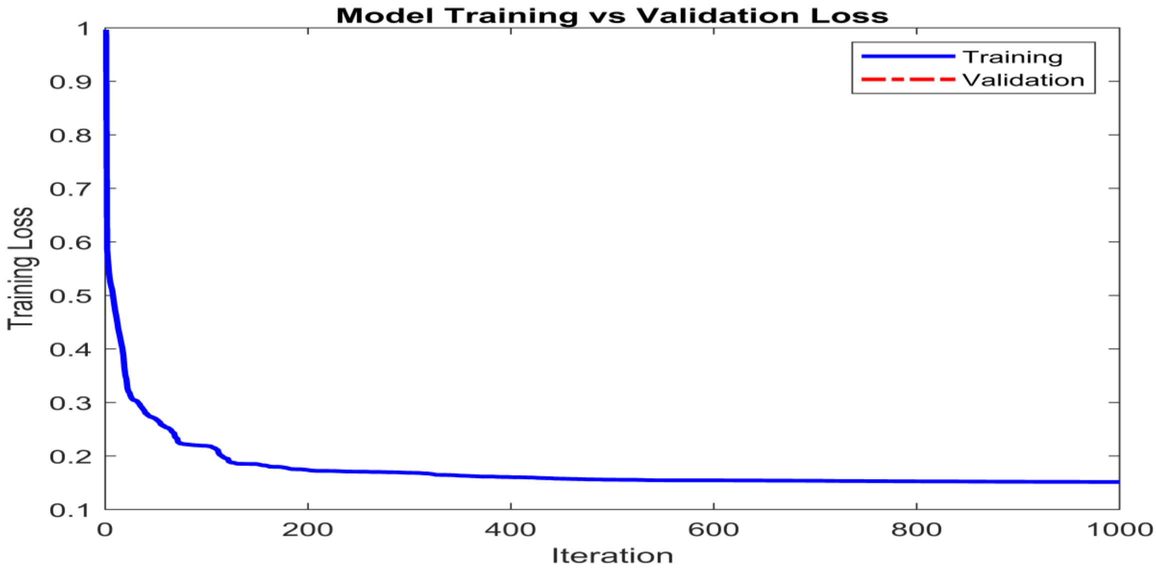

Fig. 3. Experimental procedures for sample testing and preparation

Across the models, there was a consistent and steep decline in training loss during the initial epochs, followed by stabilization at lower values. This trend indicates effective learning and minimization of prediction error. The validation loss closely followed the training loss (or was not significantly divergent), further confirming that overfitting did not occur and the models generalized well to unseen data. The final flattened portions of the curves indicate that sufficient training epochs were used and that model hyperparameters were well-tuned. Therefore, the ANN models successfully learned the complex, nonlinear relationships between material proportions and concrete properties. The convergence behavior confirms the applicability of neural networks for predictive modeling and performance optimization in the use of Ci and PPW for culvert concrete design.

a) Model Performance Evaluation and Interpretation

The predictive performance of the trained machine learning models was assessed using standard metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), Mean Squared Error (MSE), and Scatter Index (SI). The results are summarized in Table I, and interpreted below.

TABLE I. MODEL EVALUATION METRICS

Output	RMSE	MAE	R^2	MSE	Scatter Index
Compressive	0.0853	0.0701	0.9923	0.00728	0.105
Flexural	0.0883	0.0701	0.9917	0.00780	0.109
Tensile	0.0860	0.0626	0.9921	0.00740	0.106
Water Absorption	0.2735	0.2024	0.9205	0.07478	0.340
Initial Setting	0.1178	0.0985	0.9853	0.01387	0.145
Final Setting	0.0958	0.0804	0.9903	0.00918	0.118
Slump	0.1201	0.0958	0.9847	0.01442	0.148

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3.6.2 Strength Prediction Accuracy

Table I shows the models exhibited excellent predictive capability for strength related parameters: Compressive Strength: $R^2 = 0.9923$, indicating that over 99% of the variability in compressive strength was explained. Both RMSE, in Fig. 4 and MAE values were low, suggesting highly accurate and consistent predictions. Flexural and Tensile Strength: Both outputs had $R^2 > 0.991$, confirming excellent fit. Error values were similarly minimal.

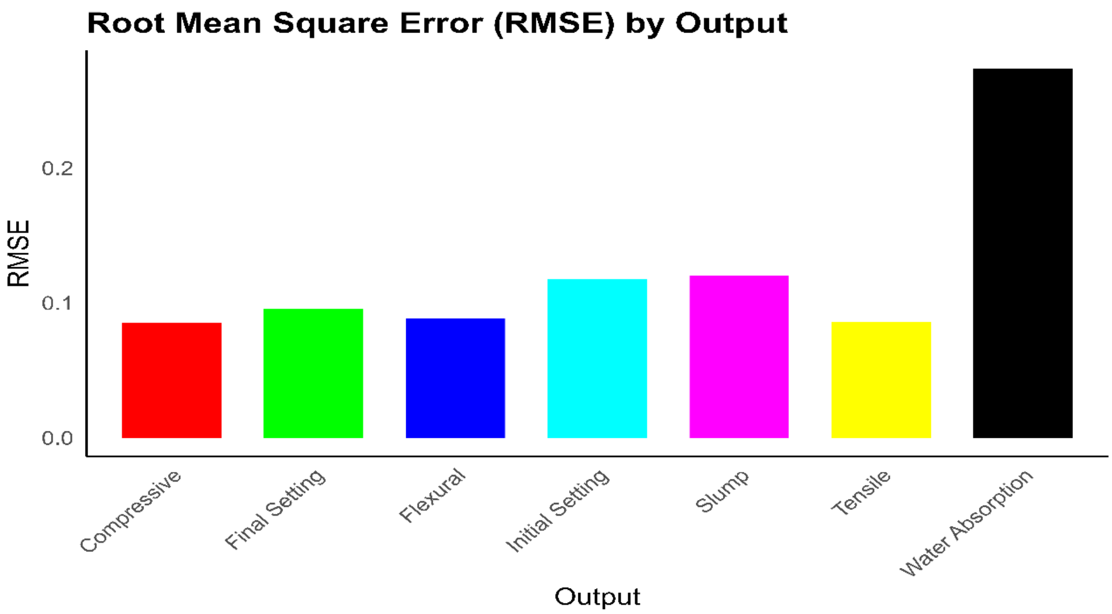

Fig. 4. Summary of performance of parameters in the model by RMSE

Initial and Final Setting Time: The models performed strongly ($R^2 = 0.9853$ and 0.9903, respectively), suggesting reliable prediction of early and final hydration behavior. Slump: With $R^2 = 0.9847$, slump prediction was also highly accurate, although marginally more variable than strength outputs. Water Absorption: This parameter showed relatively lower accuracy ($R^2 = 0.9205$), with higher RMSE in Fig. 4 and Scatter Index. This is likely due to water absorption's sensitivity to microstructural variations and plastic-related porosity not fully captured in the input features.

The model achieved outstanding performance across most output parameters, particularly in strength and setting characteristics. Slightly reduced accuracy in water absorption suggests an opportunity for further refinement by incorporating additional material characteristics such as porosity. Nevertheless, the models demonstrate excellent predictive reliability suitable for practical application in concrete mix optimization.

IV. FINDINGS

A summary of the results is presented in Table II.

TABLE II: LABORATORY RESULTS FOR VARIOUS MIX COMBINATIONS

Slump	Batch	PPW (%)	Ci (%)	Compressive	Flexural	Tensile	Water Abs. (%)	Initial Set	Final Set
117.244	OP_1	2.25	2.45	16.078	2.726	2.478	6.169	289.653	482.756
109.917	OP_2	2.25	2.40	15.073	2.640	2.407	11.739	294.050	490.083
105.239	OP_3	2.25	2.35	14.432	2.583	2.360	9.939	296.856	494.761
102.951	OP_4	2.25	2.30	14.118	2.555	2.337	10.895	298.229	497.049
96.517	OP_5	2.25	2.25	13.236	2.473	2.270	8.068	302.090	503.483
83.005	OP_6	2.20	2.50	11.383	2.294	2.121	8.235	310.197	516.995
97.179	OP_7	2.15	2.50	21.554	3.156	2.827	11.634	301.693	502.821
88.744	OP_8	2.30	2.50	19.624	3.012	2.710	11.523	306.754	511.256

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100.335	OP_9	2.35	2.50	21.199	3.130	2.806	11.361	299.799	499.665
92.308	OP_10	2.40	2.50	19.503	3.002	2.703	12.815	304.615	507.692
83.761	OP_11	2.20	2.45	17.697	2.860	2.587	12.964	309.743	16.239
75.549	OP_12	2.15	2.40	15.962	2.716	2.470	9.695	314.670	524.451
86.486	OP_13	2.10	2.35	14.047	2.548	2.332	9.744	308.108	513.514
81.297	OP_14	2.30	2.55	13.204	2.470	2.268	9.572	311.222	518.703
93.629	OP_15	2.35	2.60	11.958	2.351	2.169	8.874	03.823	506.371
85.986	OP_16	2.40	2.65	10.982	2.253	2.087	11.161	308.409	514.014
80.612	OP_17	2.45	2.70	10.296	2.182	2.027	10.945	311.633	519.388

The data was used to train ANN described in Section 3.3. A snippet of the results from R2023b is presented as Optimal Predicted Mix: PPW = 2.117%, Ci = 2.536%.

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Predicted Material Properties (Compressive ... Slump):
Compressive Flexural Tensile WaterAbsorption InitialSetting FinalSetting Slump
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23.018      2.978    2.8     0.08           294.53         485.27       112.09
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Detailed results were tabulated based on the optimization algorithm and results presented in Table III.

TABLE III. PREDICTED DATA BASED ON PROPOSED MATHEMATICAL MODEL BASED ON (1-9)

Slump	Batch	PPW %	Ci	Compressive	Flexural	Tensile	Water Absorption	Initial Setting	Final Setting
86.499		2.1	2.3625	15.232	2.598	2.466	9.696%	307.619	515.048
98.288		2.1	2.475	22.657	3.062	3.080	10.479%	297.663	504.402
81.701		2.1875	2.475	15.952	2.786	2.358	11.482%	311.184	513.363
102.774		2.275	2.475	18.317	2.865	2.611	8.777%	298.508	497.224
112.097		2.3625	2.3625	16.154	2.797	2.324	14.112%	281.585	488.934
99.874		2.3625	2.475	20.192	3.032	2.676	12.526%	299.821	501.353
114.439		2.45	2.25	15.074	2.601	2.187	14.148%	281.042	486.507
102.209		2.45	2.3625	17.624	2.833	2.299	15.055%	294.541	498.213
89.988		2.45	2.475	20.018	2.983	2.613	13.541%	307.000	510.125
84.114		2.45	2.5875	17.750	2.964	2.758	11.994%	308.328	508.051
81.653		2.1	2.3625	15.118	2.614	2.401	9.691%	308.107	514.094
91.635		2.1	2.475	22.799	3.126	2.896	10.798%	300.335	505.010
96.355		2.1	2.7	21.863	2.278	2.999	9.101%	313.765	509.087
85.869		2.1875	2.475	15.757	2.728	2.394	11.710%	308.498	510.514
106.047		2.275	2.3625	15.062	2.632	2.421	10.690%	288.557	477.698
102.047		2.275	2.475	18.318	2.907	2.611	8.926%	298.496	497.656
78.869		2.3625	2.25	15.804	2.657	2.482	9.054%	277.438	461.929
96.752		2.3625	2.3625	17.307	2.787	2.582	10.890%	280.916	462.178
98.738		2.3625	2.475	19.144	2.969	2.695	12.264%	299.322	500.410
76.193		2.45	2.25	17.703	2.811	2.624	10.154%	276.525	464.801
92.138		2.45	2.3625	19.209	2.921	2.687	15.048%	295.022	471.622
87.741		2.45	2.475	19.947	3.040	2.736	14.760%	305.883	508.633
77.547		2.45	2.5875	21.789	3.195	2.843	13.134%	309.128	507.168
105.328		2.1	2.475	21.087	2.950	2.786	12.185%	297.468	491.749
125.558		2.1	2.5875	21.018	2.420	2.610	11.514%	291.799	481.255
81.967		2.1875	2.475	16.921	2.793	2.479	10.628%	309.410	519.004
114.237		2.275	2.3625	15.096	2.651	2.373	10.737%	292.134	479.171
102.812		2.275	2.475	18.573	2.861	2.588	8.799%	298.679	497.283
124.274		2.3625	2.25	15.611	2.650	2.156	12.746%	290.940	453.606
113.414		2.3625	2.3625	16.996	2.810	2.329	12.785%	295.602	455.995
100.216		2.3625	2.475	18.871	3.004	2.694	12.297%	300.843	496.349
116.941		2.45	2.25	17.560	2.727	2.095	16.473%	297.458	443.629
103.748		2.45	2.3625	18.862	2.850	2.273	15.565%	302.212	469.650
90.569		2.45	2.475	19.652	2.958	2.610	14.304%	306.021	503.202
86.306		2.45	2.5875	22.573	3.087	2.682	12.285%	307.955	506.397

A. Paired *t*-Test: Laboratory vs ANN Predictions

Hypothesis test was performed to test is there is no statistical significance between laboratory test and the ANN-preducted values. The null hypothesis (H_0) assumes no significant difference between the lab and ANN-predicted values. A significance level of $\alpha = 0.05$ was used.

TABLE IV. PAIRED T-TEST RESULTS (LAB VS ANN PREDICTIONS)

Performance Parameter	p-value	Significance
Compressive Strength	0.44297	Not Significant
Flexural Strength	0.18671	Not Significant
Tensile Strength	0.90740	Not Significant
Water Absorption	0.48483	Not Significant
Initial Setting Time	0.67462	Not Significant
Final Setting Time	0.64172	Not Significant
Performance Index	0.49402	Not Significant
Slump	0.69313	Not Significant

As shown in Table IV, all p-values exceed the significance threshold ($p > 0.05$), indicating that the differences between lab-measured and ANN-predicted values are statistically insignificant. This supports the reliability of the ANN model in replicating experimental observations.

B. Discussion

The findings of this study reinforce the central motivation highlighted in the introduction: the need for accurate prediction of concrete strength and durability properties when using alternative cementitious and aggregate materials like cinchona industrial waste ash and pulverized plastic. As reported in the literature [9, 11, 10], machine learning techniques—particularly artificial neural networks—have been recognized for their superior performance over classical regression approaches in handling complex nonlinear interactions in multi-component concrete systems.

The ANN model developed in this study achieved high accuracy across key outputs: Compressive Strength ($R^2 = 0.992$, RMSE = 0.085): consistent with prior results by [9] and [14], where ANN models predicted strength within $\pm$5 MPa error range. Flexural and Tensile Strength ($R^2 \approx 0.992$): high reliability was achieved, matching findings by [13] using genetic programming. Setting Times ($R^2 > 0.985$): prediction of initial and final setting times—parameters rarely explored in other models, demonstrated the versatility of the developed ANN approach. Workability and Durability (e.g., slump and water absorption): although slightly lower in R^2 (about 0.92 for water absorption), the ANN model still provided acceptable accuracy.

These outcomes confirm that ANN can effectively simulate the performance behavior of concrete mixtures incorporating waste-derived materials. This aligns with literature that emphasized ANN's robustness in generalizing complex material-property relationships [10, 14]. Compared to traditional regression models such as those used by [8] and [7], the ANN-based model in this study demonstrated consistently lower scatter index and error margins, establishing it as more suitable for real-world application in concrete mix optimization.

V. CONCLUSION

This study successfully developed and validated ANN-based predictive models for estimating the mechanical and durability properties of concrete incorporating cinchona ash and pulverized plastic waste. The model demonstrated excellent accuracy across compressive, tensile, and flexural strength metrics, with R^2 values exceeding 0.98 and scatter indices well below 0.15. The best performance was observed in strength parameters, while durability indicators like water absorption had slightly higher variability. The models demonstrated the feasibility of optimizing concrete mixes using industrial waste, supporting circular economy principles. Future studied can extend the model to include additional parameters like durability under aggressive environments (e.g., chloride ingress, carbonation). Incorporate other waste materials (e.g., fly ash, ceramic dust) to generalize the model's applicability.

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