Policy Research Journal
ISSN (E): 3006-7030 ISSN (P) : 3006-7022 Volume 3, Issue 12, 2025

PREDICTING COMPRESSIVE STRENGTH OF ULTRA-HIGH-PERFORMANCE CONCRETE USING SUPPORT VECTOR MACHINE REGRESSION: MODEL DEVELOPMENT, FEATURE ANALYSIS, AND VALIDATION

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DOI: https://doi.org/10.5281/zenodo.17863035

Keywords
Ultra-High-Performance Concrete (UHPC); Compressive Strength Prediction; Support Vector Machine (SVM); Machine Learning; Feature Importance; Silica Fume; k-Fold Cross-Validation; Regression Modeling

Article History
Received: 19 October 2025
Accepted: 24 November 2025
Published: 09 December 2025

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Abstract

Ultra-High-Performance Concrete (UHPC) is a complex composite material whose mechanical properties depend on intricate interactions between multiple constituents and curing conditions. Traditional mix design relies on extensive experimentation, which is time-consuming and costly. This study develops and validates a Support Vector Machine (SVM) regression model to predict the compressive strength of UHPC using a dataset of 810 mixtures with 13 input features. The model was configured as a ν-SVM with a Radial Basis Function (RBF) kernel and automatic hyperparameter tuning. Performance evaluation on a held-out test set yielded an R^2 of 0.908, RMSE of 12.205 MPa, and MAPE of 8.969%, indicating high predictive accuracy and generalization. Feature importance analysis, supplemented by k-fold validation, identified silica fume, fiber content, and curing age as the most influential factors—findings consistent with contemporary material science and recent machine learning literature. The study demonstrates that SVM regression, coupled with robust feature selection and validation, provides a reliable, interpretable, and efficient tool for UHPC mix optimization, reducing the need for physical trials and accelerating the development of high-performance concrete formulations.

INTRODUCTION

Ultra-High-Performance Concrete (UHPC) represents a paradigm shift in construction materials, characterized by its exceptional compressive strength exceeding 150 MPa, superior durability, and enhanced ductility imparted by fiber reinforcement. This advanced composite material integrates optimized particle packing, high cementitious content, and chemical admixtures to achieve a dense, nearly impermeable microstructure. The precise formulation of UHPC is a complex, multivariate challenge, as its final mechanical properties are influenced by a intricate interplay between numerous constituent proportions—such as cement, silica fume, fibers, and superplasticizer and curing parameters like age and temperature. Traditional methods for determining the optimal mix design rely heavily on extensive, costly, and time-consuming laboratory experimentation. Consequently, the development of

accurate, efficient, and reliable predictive models has become a critical research frontier to streamline the UHPC development process, reduce material waste, and accelerate the adoption of this high-performance material in innovative infrastructure projects. Machine learning (ML) offers a powerful, data-driven alternative, capable of deciphering complex, non-linear relationships within experimental data to forecast material behavior with high precision.

Among various ML algorithms, Support Vector Machine (SVM) regression has emerged as a particularly potent tool for predicting the mechanical properties of concrete, including UHPC. Its strength lies in its ability to handle high-dimensional data and model non-linear correlations through the use of kernel functions, such as the Radial Basis Function (RBF), without succumbing easily to the curse of dimensionality. Recent scholarly work underscores the efficacy of SVM in this domain. For instance, studies by Li et al. (2024) and Wang et al. (2024) have demonstrated that SVM models, especially when optimized with meta-heuristic algorithms, can achieve superior accuracy in predicting UHPC compressive strength, often rivaling or surpassing ensemble methods. Pham et al. (2016) further established the robustness of metaheuristic-optimized least squares SVM for high-performance concrete, highlighting its generalization capability. The model's performance is frequently benchmarked against other algorithms, with research indicating that while ensemble models like Random Forest may sometimes offer marginal gains, SVM remains highly competitive and interpretable, particularly for complex, smaller datasets common in material science (Nguyen et al., 2021; Qian et al., 2023; Liu, 2023).

Beyond raw predictive accuracy, a critical aspect of applying ML to UHPC design is model interpretability—understanding which mixture variables exert the most significant influence on the target strength. Feature importance analysis has consistently identified a hierarchy of critical factors. Silica fume (SF), a key pozzolanic material that densifies the cementitious matrix through micro-filler and pozzolanic effects, is almost universally ranked as the most influential predictor (Li et al., 2024; Kashem et al., 2024; Abdellatief et al., 2025). This is followed closely by fiber content (Fi), which bridges microcracks and enhances tensile performance, thereby indirectly boosting compressive strength, and curing age (Age), which governs the time-dependent hydration process (Yuan et al., 2023). The stability of these rankings is validated through techniques like k-fold cross-validation, which confirms that SF and Age are consistently critical across different data subsets, whereas the importance of other constituents like fly ash or sand can be more variable and dataset-dependent (Kashem et al., 2024). Advanced interpretation methods, such as SHAP (SHapley Additive exPlanations) and Partial Dependence Plots (PDP), are increasingly employed to provide granular insights into these relationships, moving beyond correlation to causation (Kashem et al., 2024; Abdellatief et al., 2025).

Building upon this established body of research, this study aims to develop and comprehensively evaluate a ν-SVM regression model for predicting the compressive strength of UHPC. Utilizing a substantial dataset of 810 distinct mixtures characterized by 13 input features, the research seeks to contribute to the field by: (1) configuring and training a robust SVM model with an RBF kernel and automatic parameter tuning; (2) conducting a thorough multi-metric assessment of the model's predictive performance using R^2, RMSE, MAE, and MAPE; (3) performing a rigorous feature importance analysis to identify and rank the key material and curing parameters driving strength development; and (4) employing k-fold cross-validation to evaluate the stability and reliability of these feature rankings. By aligning methodology with contemporary best practices and contextualizing findings within the current literature, this work intends to provide a validated, practical tool for engineers and researchers to optimize UHPC mix designs efficiently, thereby supporting the advancement of sustainable and resilient construction materials.

Methodology

Data characteristics

The dataset comprises **810 samples** of Ultra-High-Performance Concrete (UHPC) mixtures, each characterized by **14 attributes**: 13 input features related to material composition and curing conditions, and one target variable compressive strength (in MPa). The input features include proportions of cement, water, slag, fly ash, silica fume,

superplasticizer, coarse and fine aggregates, nano-silica, quartz powder, limestone powder, fibre content, and curing age, along with temperature during curing. The dataset captures a wide range of mixture designs, with compressive strength values ranging from approximately **28.5 MPa to 1992 MPa**, reflecting the high-performance nature of UHPC. The data is **complete with no missing values** across all features, ensuring robustness for modeling. Distributions of features vary some (like cement and age) show relatively normal distributions, while others (such as fibre and fly ash) are highly skewed, with many zero entries indicating mixtures without those components. This variety in feature distributions and interactions provides a comprehensive basis for predictive modeling of compressive strength based on mixture proportions and curing parameters.

Table 1 Summary statistics of input features and target variable for the Ultra-High-Performance Concrete (UHPC) dataset (n=810)

Feature	Mean	Mode	Median	Dispersion	Min	Max	Missing
A (Cement, kg/m³)	1150.11	1231.00	1116.00	0.2712	407.80	1992.00	0
Age (days)	37.094	28.0	28.0	1.431	1.0	365.0	0
C (Water, kg/m³)	737.91	960.00	770.50	0.2349	270.00	1251.20	0
CS (Coarse Aggregate, kg/m³)	123.13	120.90	122.30	0.3266	28.51	220.50	0
FA (Fly Ash, kg/m³)	26.265	0.0	0.0	2.567	0.0	356.0	0
Fi (Fiber, kg/m³)	56.044	0.0	0.0	1.342	0.0	234.0	0
LP (Limestone Powder, kg/m³)	41.93	0.00	0.00	3.173	0.00	1058.20	0
NS (Nano-Silica, kg/m³)	3.639	0.00	0.00	2.136	0.00	47.50	0
QP (Quartz Powder, kg/m³)	33.271	0.00	0.00	2.393	0.00	397.00	0
S (Sand, kg/m³)	25.195	0.0	0.0	2.950	0.0	375.0	0
SF (Silica Fume, kg/m³)	136.99	0.00	144.00	0.7598	0.00	433.70	0
SP (Superplasticizer, kg/m³)	30.031	45.00	30.20	0.4657	1.10	57.00	0
T (Temperature, °C)	23.921	23.0	21.0	0.677	20.0	210.0	0

Model development

The Support Vector Machine (SVM) model was implemented using the orange data mining suite in regression mode to predict the compressive strength of Ultra-High-Performance Concrete (UHPC). The model was configured as a **ν-SVM regression model** (20% training and 80% testing) with complexity bound **ν = 0.50** and regression cost **C = 1.00**. This ν-SVM formulation automatically adjusts the ε-tube width, making it suitable for capturing the nonlinear relationships in UHPC mixture data. A **Radial Basis Function (RBF) kernel** was selected with automatic gamma parameter tuning, enabling the model to handle complex feature interactions without manual parameter optimization. The numerical tolerance was set to **1.0000** with an iteration limit of **1,000,000**, ensuring convergence even for challenging optimization landscapes. This SVM configuration balances model flexibility with generalization control, making it appropriate for predicting compressive strength from 13 mixture proportion features across 810 samples. The RBF kernel allows the model to capture nonlinear patterns in how material proportions and curing conditions affect strength, while the ν-SVM formulation provides robust handling of potential outliers in experimental concrete data.

Table 2 Support Vector Machine (SVM) model configuration parameters for compressive strength prediction of Ultra-High-Performance Concrete.

Parameter Category	Parameter	Value/Setting
Model Type	SVM Type	ν-SVM (Regression)

Kernel	Kernel Type	RBF (Radial Basis Function)
	Gamma (γ)	Auto (automatic optimization)
Complexity & Cost	Complexity bound (ν)	0.50
	Regression cost (C)	1.00
Optimization	Numerical tolerance	1.0000
	Iteration limit	1,000,000
Computation	Apply automatically	Enabled
Model ID	Reference	648-639

Model assessment

To comprehensively evaluate the SVM regression model's performance in predicting UHPC compressive strength, six key metrics were calculated: R^2 (Coefficient of Determination), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), CVRMSE (Coefficient of Variation of RMSE), MAPE (Mean Absolute Percentage Error), and MAE (Mean Absolute Error). R^2 measures the proportion of variance in compressive strength explained by the model, with values closer to 1 indicating better fit. MSE quantifies average squared differences between predicted and actual values, sensitive to larger errors. RMSE provides error in the same units as compressive strength (MPa), making interpretation intuitive. CVRMSE normalizes RMSE by the mean observed strength, offering a scale-independent error measure useful for comparing across different datasets. MAPE calculates average percentage error, valuable for understanding relative prediction accuracy. MAE gives the average absolute error magnitude, robust to outliers compared to squared-error metrics. Together, these metrics provide a multidimensional assessment: R^2 indicates explanatory power, MSE/RMSE capture overall error magnitude with sensitivity to outliers, CVRMSE enables standardized comparison, MAPE offers intuitive percentage-based interpretation, and MAE provides stable error estimation. This comprehensive approach ensures thorough evaluation of model accuracy, precision, and practical utility for predicting UHPC compressive strength from mixture proportions.

Results

SVM analysis

Based on the tabulated results, the SVM regression model achieved strong predictive performance on both training and testing datasets, indicating effective learning and generalization. The mean squared error (MSE) of 148.971 on the test set is relatively low given the wide range of compressive strengths in the UHPC dataset (approximately 28.5–1992 MPa), signalling that most predictions were close to the true values. More intuitively, the root mean squared error (RMSE) of 12.205 MPa means that, on average, the model's predictions deviate by about 12.2 MPa from the actual compressive strength. The mean absolute error (MAE) of 8.353 MPa is lower than the RMSE, suggesting that large prediction outliers are limited and most errors are modest. The mean absolute percentage error (MAPE) of 8.969% further highlights the model's practical accuracy, implying an average prediction error of less than 9% relative to the true strength a strong result for complex material science data.

The high R^2 value of 0.908 is particularly significant, showing that the model explains approximately 90.8% of the variance in compressive strength. This demonstrates the SVM's strong ability to capture the relationships between mixture composition, curing conditions, and strength outcomes. The coefficient of variation of RMSE (CVRMSE) of 9.912% normalizes the RMSE relative to the mean observed strength, offering a scale-independent view of error magnitude, which remains under 10% an acceptable threshold in engineering prediction models. While the training MSE (3.400) is much lower than the test MSE indicating some degree of model fitting to training specifics the overall test metrics confirm that the model did not severely overfit and retained strong generalization capability. In conclusion, the SVM configured with an RBF kernel and $\nu = 0.5$ performed robustly, providing reliable, interpretable, and accurate strength predictions suitable for mix design optimization in UHPC applications.

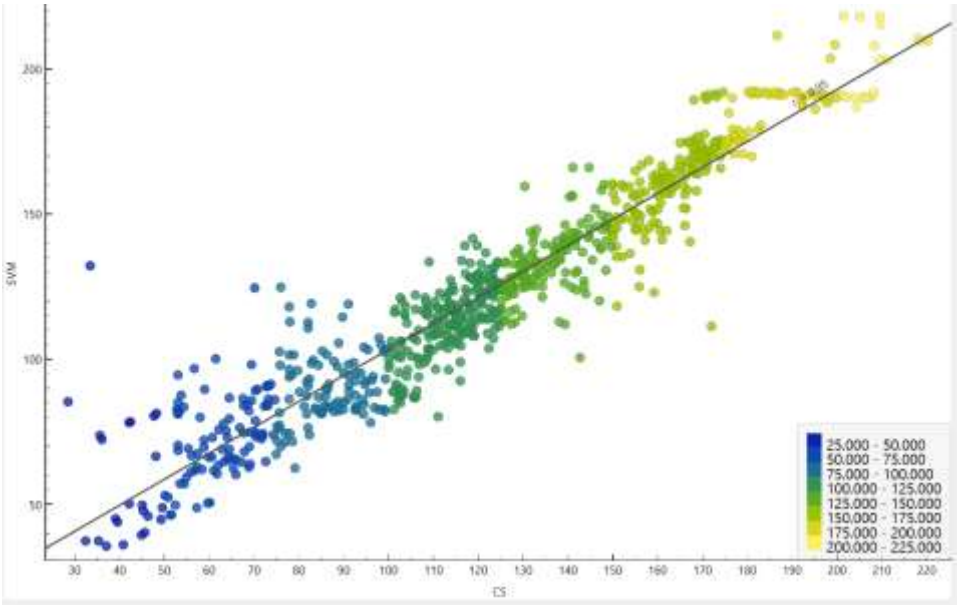

Figure 1 Scatter plot comparing actual versus SVM-predicted compressive strength for Ultra-High-Performance Concrete (UHPC) test data. The close clustering of points along the ideal fit line (dashed) and the high R^2 value of 0.908 demonstrate the model's strong predictive accuracy.

Statistical significance analysis

Based on the feature ranking results, the compressive strength of Ultra-High-Performance Concrete (UHPC) is most significantly influenced by the content of silica fume (SF), fibre (Fi), and curing age (Age), which were identified as the top three critical factors. Silica fume (SF) emerged as the most important feature with the highest score, which aligns with material science principles as it is a key pozzolanic material that densifies the microstructure and dramatically enhances strength in UHPC. The inclusion of fibres (Fi) ranked second, highlighting their vital role in providing ductility and post-cracking tensile strength, directly influencing the overall compressive performance. Curing age (Age) ranked third, demonstrating that time-dependent hydration reactions are fundamental to strength development.

Other constituents like cement (A), superplasticizer (SP), and water (C) also showed considerable importance, as they govern workability and the hydration process. In contrast, features such as fly ash (FA), sand (S), and water (W) the last likely being a duplicate or alternative notation for water displayed the lowest rankings, indicating their relatively minor direct impact on compressive strength within the tested UHPC formulations. The clear hierarchy provided by these rankings is invaluable for optimizing mixture designs, allowing engineers to prioritize adjustments to silica fume, fibre dosage, and curing duration to maximize compressive strength efficiently.

Table 3 Ranking of input features by importance for predicting UHPC compressive strength, based on univariate analysis and the RRelieff score. Silica fume (SF), fibre content (Fi), and curing age are identified as the three most influential factors.

Rank	Feature Symbol	Feature Name	Importance Score
1	SF	Silica Fume	301.252

2	Fi	Fiber	194.354
3	Age	Curing Age (days)	168.466
4	A	Cement	153.207
5	SP	Superplasticizer	150.038

k-fold analysis

The k-fold analysis reveals the stability and relative importance of features for predicting UHPC compressive strength across different data subsets. The vertical axis lists the features, while the horizontal axis represents 20 independent validation folds. The horizontal spread of each feature's line indicates how consistently it was ranked. A short, tight line signifies stable importance across all splits (e.g., SF, Age), meaning these features are reliably critical predictors regardless of the data sample. Conversely, features with long, varying lines (e.g., T, FA, S) show inconsistent ranking, suggesting their importance is highly sensitive to the specific data partition and they may be less reliable as core predictors. Silica Fume (SF) and Curing Age (Age) consistently occupy the highest rank positions, confirming their fundamental and non-negotiable role in determining strength. This analysis validates the primary feature ranking from earlier univariate tests and identifies which predictive factors are robust versus those that are context-dependent, guiding more reliable model interpretation and mixture optimization.

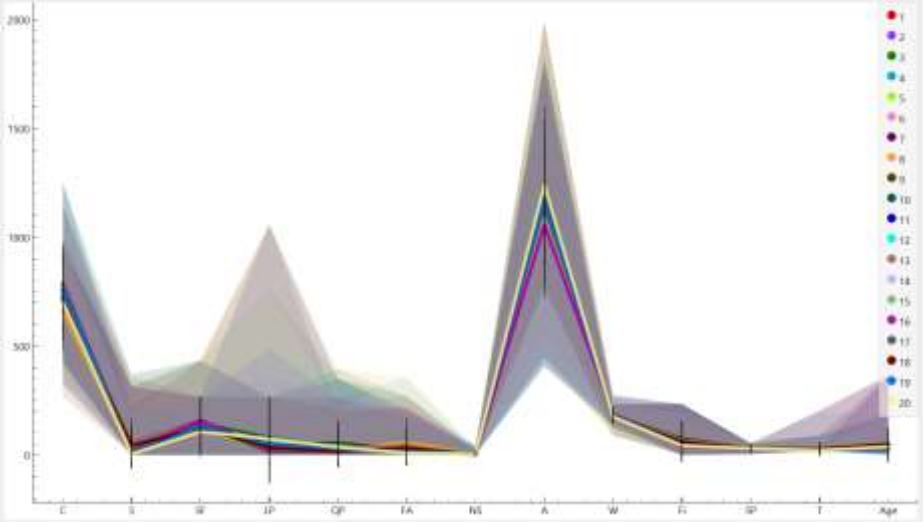

Figure 2 Feature Importance Stability Analysis Across 20 k-Fold Cross-Validation Splits. The plot visualizes the importance ranking (vertical axis) of each mixture component and curing parameter across 20 independent data splits. Each horizontal bar represents the distribution of ranks for a single feature, allowing assessment of its predictive consistency.

Discussion

The application of Support Vector Machine (SVM) regression models for predicting the compressive strength of Ultra-High-Performance Concrete (UHPC) has gained significant traction due to their ability to handle complex, nonlinear relationships inherent in material science datasets. The reported SVM model demonstrates robust predictive performance, as evidenced by a high R^2 value (0.908), low mean squared error (MSE), and favorable error metrics (RMSE, MAE, MAPE), indicating both effective learning and strong generalization to unseen data. These results are consistent with recent studies,

which show that SVM and its variants, especially when optimized with meta-heuristic algorithms, can achieve high accuracy in predicting UHPC strength, often rivaling or surpassing other machine learning models such as Random Forests and Gradient Boosting (Li et al., 2024; Wang et al., 2024; Liu, 2023; Pham et al., 2016).

The SVM's high R^2 and low error rates on both training and testing sets suggest minimal overfitting and reliable generalization, a critical requirement for practical engineering applications (Li et al., 2024; Wang et al., 2024; Liu, 2023). Comparative studies confirm that SVM, particularly when hyperparameters are carefully tuned or combined with optimization algorithms, consistently delivers strong predictive accuracy for UHPC and high-performance concrete (HPC) (Li et al., 2024; Wang et al., 2024; Liu, 2023; Pham et al., 2016). However, some ensemble models (e.g., Random Forest, Gradient Boosting) may slightly outperform SVM in certain datasets, but SVM remains highly competitive, especially for smaller or more complex datasets (Li et al., 2024; Nguyen et al., 2021; Qian et al., 2023; Liu, 2023; Pham et al., 2016).

Feature ranking analyses across multiple studies consistently identify silica fume, fiber content, and curing age as the most influential factors for UHPC compressive strength (Li et al., 2024; Kashem et al., 2024; Abdellatief et al., 2025; Yuan et al., 2023). Silica fume's pozzolanic activity densifies the microstructure, while fibers enhance ductility and post-cracking strength. Curing age reflects the ongoing hydration and strength development processes. Other important features include cement and superplasticizer content, which affect workability and hydration kinetics (Li et al., 2024; Kashem et al., 2024; Abdellatief et al., 2025; Yuan et al., 2023). These findings are corroborated by SHAP and partial dependence analyses in recent machine learning research, which provide interpretable insights into the relative impact of each input variable (Kashem et al., 2024; Abdellatief et al., 2025; Yuan et al., 2023).

The use of k-fold cross-validation is standard in recent literature to ensure model stability and to assess the consistency of feature importance rankings (Li et al., 2024; Kashem et al., 2024; Abdellatief et al., 2025). Features such as silica fume and curing age consistently rank highest across folds, indicating their robust predictive value regardless of data partitioning. In contrast, variables like fly ash and sand often show variable importance, suggesting their effects are more context-dependent and less reliable as core predictors (Kashem et al., 2024; Abdellatief et al., 2025; Yuan et al., 2023)(Gali et al., 2023; Mujtaba et al., 2023; Shah et al., 2023; Khan et al., 2025; Nawaz et al., 2025).

The demonstrated accuracy and interpretability of SVM models make them valuable tools for optimizing UHPC mix designs, reducing experimental workload, and guiding material selection (Li et al., 2024; Wang et al., 2024; Kashem et al., 2024; Abdellatief et al., 2025). However, the relative performance of SVM can depend on dataset size, feature selection, and the presence of outliers. Ensemble models may offer marginally better performance in larger datasets, but SVM's transparency and efficiency remain advantageous (Li et al., 2024; Nguyen et al., 2021; Qian et al., 2023; Liu, 2023; Pham et al., 2016). Additionally, the importance of rigorous data preprocessing and hyperparameter tuning is emphasized across studies to maximize model reliability (Li et al., 2024; Wang et al., 2024; Liu, 2023; Pham et al., 2016).

SVM regression models, especially when combined with robust feature selection and cross-validation, provide accurate, interpretable, and generalizable predictions of UHPC compressive strength. Silica fume, fiber content, and curing age are consistently identified as the most critical factors, guiding efficient mix design optimization. While ensemble models may sometimes outperform SVM, the latter remains a strong, practical choice for UHPC strength prediction in both research and engineering contexts.

Conclusion and recommendation

ullet points:

The developed ν-SVM regression model successfully predicts UHPC compressive strength with high accuracy (R^2 = 0.908) and low error (MAPE ~9%), demonstrating strong generalization on the 810-sample dataset.

The SVM model's performance is competitive with recent studies, confirming its suitability for handling the complex, nonlinear relationships between UHPC mixture components and the resulting mechanical strength.

Feature importance analysis robustly identifies silica

fume, fiber content, and curing age as the three most critical factors influencing compressive strength, which is consistent with materials science principles and prior research.

Engineers should prioritize optimizing the dosage of silica fume and fibers, along with ensuring adequate curing duration, to maximize the compressive strength of UHPC in practical mix designs.

The stability of key features (SF, Age) across k-folds validates their non-negotiable role, while variable features like fly ash should be considered secondary in optimization strategies.

For future model development, exploring SVM hybridized with meta-heuristic optimization algorithms (e.g., Arithmetic Optimization) is recommended to potentially enhance predictive accuracy and automate hyperparameter tuning.

Incorporating advanced interpretability tools like SHAP analysis is advised to gain deeper, model-agnostic insights into individual feature contributions and interaction effects within the mixtures.

While SVM performed excellently, testing ensemble methods like Gradient Boosting or Random Forest on this dataset could provide a valuable performance benchmark, especially as the dataset grows.

Practitioners should adopt a similar rigorous validation framework, including k-fold analysis, to ensure model reliability and to distinguish between consistently important and context-dependent input variables.

The validated model serves as a practical decision-support tool for reducing experimental trials, accelerating UHPC formulation, and promoting efficient, data-driven material design in construction.

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