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Impact of Temperature on Concrete Properties: A Machine Learning Approach for Structural Design

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Abstract

Elevated temperatures significantly reduce the mechanical performance and durability of concrete, leading to microstructural damage, strength loss, and reduced service life. This study investigates the combined effects of temperature, water-cement (w/c) ratio, and cooling conditions on residual compressive strength using machine learning (ML) for performance-based structural design. A dataset of 135 samples from published literature, covering 25°C to 900°C under varied mix designs and cooling regimes, was used to train and validate four ML algorithms Lasso Regression, Random Forest (RF), Extreme Gradient Boosting (XGBoost), and Support Vector Regression (SVR) evaluated with Coefficient of Determination (R^2), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Results indicate that Random Forest performs best, providing high predictive accuracy and robustness in modeling nonlinear degradation patterns. Lasso Regression highlighted temperature as the most influential factor, while XGBoost and SVR also achieved reliable predictions. Validation with M20 and M30 grade concrete data showed close agreement between measured and predicted strengths. Strength retention dropped sharply beyond 400°C, with substantial losses at higher temperatures. The findings demonstrate that ML models, particularly RF, can minimize the need for extensive laboratory testing while enabling rapid, reliable post-fire strength assessments of concrete compressive strength.

Keywords: *Machine Learning, Compressive Strength, Temperature Effects, Structural Design.*

1 Introduction

In civil and structural engineering, understanding the behavior of concrete at elevated temperatures is essential for ensuring structural safety in scenarios such as industrial heating, fire exposure, and extreme climatic conditions. High thermal exposure can lead to chemical decomposition, microstructural damage, and substantial loss of mechanical strength (Khaliq & Kodur, 2011; Hertz, 2003), with performance deterioration strongly influenced by the water-cement (w/c) ratio, which governs porosity, permeability, and thermal resistance (Neville, 2011; Phan et al., 2001). Cooling methods, particularly air cooling and water quenching, further affect residual strength and crack propagation (Chan et al., 2000; Castillo & Durrani, 1990). While traditional experimental studies have advanced understanding, they are often resource-intensive and limited in scope (Kodur & Sultan, 2003; Xiao et al., 2006). Machine learning (ML) offers a robust alternative, enabling prediction of complex, nonlinear relationships between temperature, mix parameters, and strength retention (Gandomi & Alavi, 2013; Ahmed et al., 2021). Algorithms such as Lasso Regression, Random Forest, XGBoost, and Support Vector Regression have shown strong predictive capabilities in material property modeling (Zhong et al., 2022). This study develops ML models trained on experimental and published datasets to predict residual compressive strength of concrete exposed to temperatures up to 1200°C, supporting performance-based design and rapid post-fire assessment.

2 Methodology

The proposed methodology, illustrated in Figure 1, follows a structured workflow to predict material properties under varying temperatures using machine learning. It starts with data collection from experimental and reliable secondary sources, followed by data preprocessing to clean, normalize, and prepare datasets. Feature engineering identifies and extracts influential variables for model development and training. Model validation ensures robustness, and evaluation metrics assess performance accuracy. The prediction and interpretation stage provides insights, which are compared with laboratory test results for verification. Finally, documentation ensures clarity, transparency, and reproducibility, making the process suitable for both academic research and practical engineering applications.

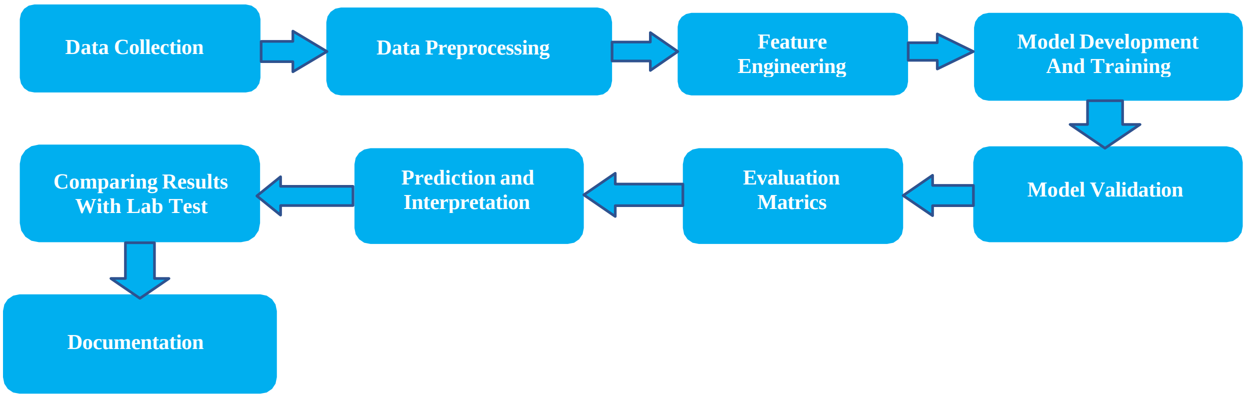


Figure 1. Flow Diagram of Methodology

2.1 Data Collection

In this study, data collection was carried out through an extensive review of published experimental works, peer-reviewed journals, and thesis archives related to the behaviour of concrete under elevated temperatures. A total of 135 samples were compiled from over 9 reliable sources, including foundational works by (Guo, Shi, & Shi, 2011; Hertz, 2003; Khoury, 1992; Noumowe, 2005), and others. These samples include measurements of residual compressive strength after thermal exposure, mix composition details (e.g., cement content, water-cement ratio), and information about cooling conditions following heating. Table 1 presents raw data extracted from reliable sources. Data were validated, normalized to SI units, and missing values imputed using linear interpolation. The cleaned dataset, stored in CSV format, was prepared for machine learning in Python using Scikit-learn and XGBoost, executed on Google Colab.

Table 1. Collected Datasets

No	Reference	# Mixes	% Data
1	Babalola et al., 2021	24	17.78%
2	Gernay et al., 2022	4	2.96%
3	Guo, Shi, & Shi, 2011	11	8.15%
4	Noumowe, 2005c	6	4.44%
5	Khoury et al., 1992	20	14.81%
6	Hertz, 2003b	15	11.11%
7	Chan et al., 2000b	18	13.33%
8	Uddin & Das, 2023c	12	8.89%
9	Chou & Pham, 2015a	25	18.53%
	Total	135	100.00%

2.2 Selection of Features and Variables

The feature selection was guided by domain knowledge and literature. Key variables include Temperature (°C), ranging from 25 to 800°C, as the primary factor affecting concrete strength. Water-Cement Ratio (W/C) influences initial strength and porosity, impacting strength loss under heat. Cooling Condition, encoded categorically, reflects post-heating effects like thermal shock. Cement Content (kg/m^3) indicates binder quantity and thermal stability. The dependent variable is Residual Compressive Strength (MPa), representing concrete's final strength after thermal exposure. Table 2 presents the datasets distribution, showing temperature values ranging from 25°C to 800°C and compressive strength from 9.6 to 56.4 MPa. The water-cement ratio varies between 0.32 and 0.74, while cement content ranges from 240 to 560 kg/m^3.

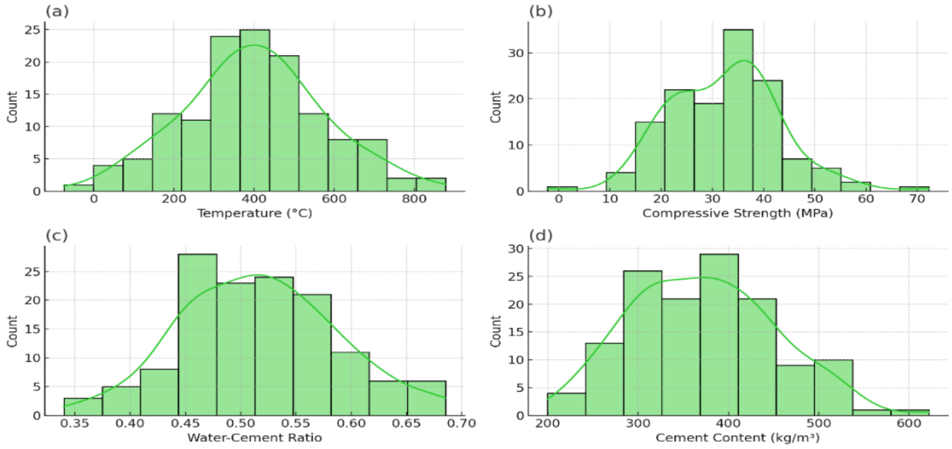


Figure 2. Distribution of Datasets (a) Sample Vs Temparature (b) Sample Vs Compressive Strength (c) Sample Vs W/C ratio (d) Sample Vs Cement Content

2.3 Correlation Analysis

The correlation matrix in Figure 3 indicates very weak linear relationships between key variables and residual compressive strength. Temperature shows a very weak positive correlation with strength (0.06), while the water-cement ratio exhibits a similarly weak positive correlation (0.08). In contrast, cement content has a very weak negative correlation with strength (-0.06). Among the input variables, the highest correlation is observed between temperature and cement content (0.12), followed by a weak negative correlation between water-cement ratio and temperature (-0.11). These weak correlations suggest complex, non-linear interactions, underscoring the need for machine learning models.

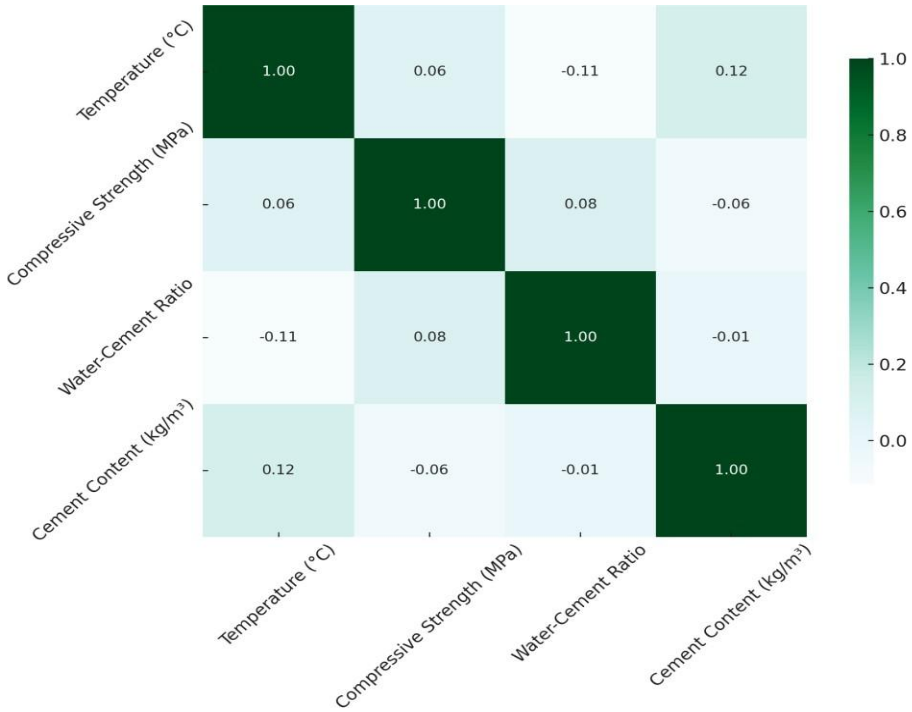


Figure 3. Correlation matrix

2.4 Model Training, Testing and Validation

This study evaluated machine learning models Lasso Regression, Random Forest, XGBoost, and SVR using R^2, RMSE, and MAE. R^2 indicates model fit, with values ≥0.95 considered excellent. RMSE penalizes large errors, while MAE measures average error magnitude, both with lower values indicating better accuracy. The dataset of 135 samples was split into 70% training, 15% validation, and 15% testing sets, ensuring robust model training and fair evaluation. This approach balances relative and absolute metrics for reliable prediction of residual compressive strength under thermal exposure.

2.5 Experimental Data to Validate ML Models

Two concrete grades, M20 and M30, were prepared following standard procedures. M20 used a nominal mix ratio of 1:1.5:3 (cement: sand: coarse aggregate) for 20 MPa strength. M30 was a laboratory-designed mix proportions determined through the Absolute Volume Method based on ACI 211.1 and IS 10262 guidelines, targeting ≥30 MPa. Both maintained a water- cement ratio of 0.45. Cylindrical molds (4" diameter × 8" height) per ASTM C39 and ISO 1920-3 were used. Specimens were compacted to reduce voids. After casting, samples cured 28 days in water, then exposed to controlled temperatures (200–600°C) before air cooling and compressive strength testing per ASTM and ISO standards. Figure 4-7 shows the practical procedure of the study. Subsequently, the compressive strength of the concrete was determined using a Universal Testing Machine (UTM).

Figure 4. Materials Preparation and Mixing

Figure 5. Mold Preparation and Casting

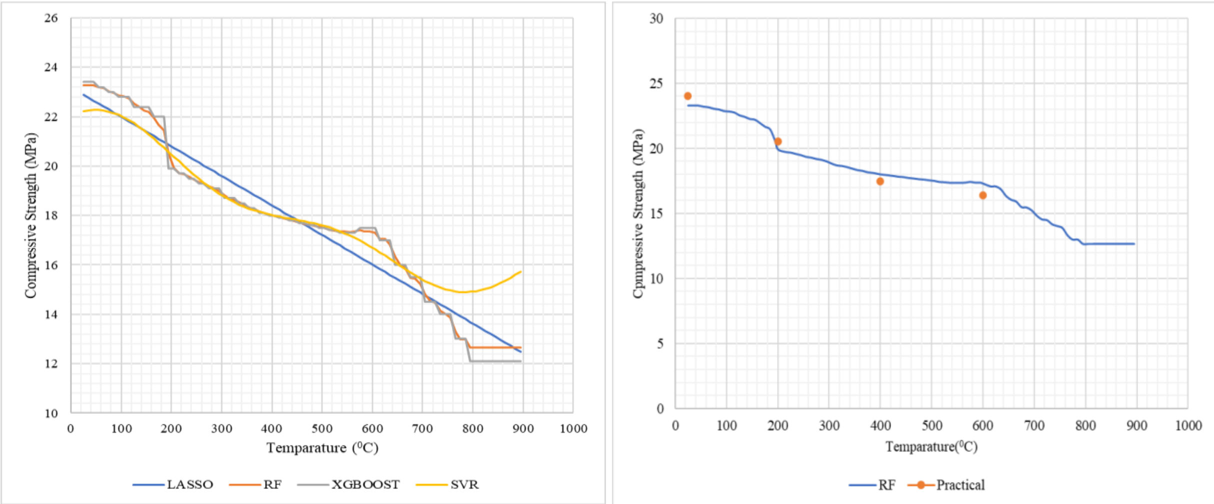
Figure 6. Curing of Specimen

Figure 7. Thermal Exposure of Specimen

3 Results and Discussions

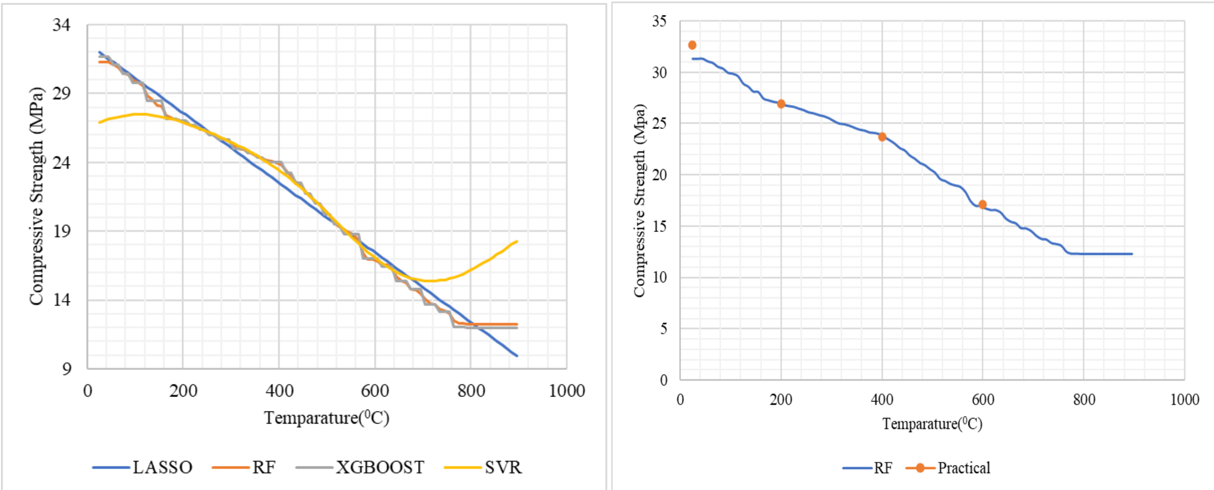
Figures 8 and 9 illustrate the predictive performance of machine learning models for M20 and M30 grade concretes exposed to elevated temperatures. For M20 concrete, all models—LASSO, Random Forest (RF), XGBoost, and SVR—show a consistent decline in compressive strength with rising temperature, reflecting experimental thermal degradation trends. Figure 8(a) reveals that RF and XGBoost follow the experimental pattern closely, while LASSO maintains a nearly linear decrease and SVR diverges beyond 500 °C, indicating reduced stability at higher temperatures. Figure 8(b) confirms RF's superior alignment with the practical data, reproducing measured strength loss across the temperature range. LASSO yields an R^2 of 0.91384, limited by its linear assumption. RF achieves exceptional accuracy with R^2 = 0.99542, RMSE = 0.20354, and MAE = 0.18362, successfully capturing subtle non-linear strength variations. XGBoost performs well (R^2 = 0.98562), effectively modeling complex relationships, whereas SVR underperforms (R^2 = 0.94446) and unrealistically rises beyond 700 °C. Experimentally, M20 concrete loses 31.86 % of its compressive strength at 600 °C; RF replicates this reduction most accurately, confirming its predictive reliability.

For M30 concrete, similar behavior is evident. Figure 9(a) shows RF and XGBoost matching the observed non-linear degradation, especially beyond 600 °C where sharp strength loss occurs due to aggregate and paste deterioration. LASSO retains a linear approximation, underestimating loss after 700 °C, while SVR displays an unrealistic upward trend beyond 800 °C caused by sensitivity to sparse data. Figure 9(b) further validates RF's precision, as its predictions almost coincide with experimental points across the temperature domain. RF maintains R^2 values between 0.99542–0.99573 with minimal RMSE and MAE, while XGBoost remains a strong secondary performer despite minor fluctuations after 400 °C. LASSO performs steadily but lacks non-linear adaptability, and SVR proves unsuitable for extreme thermal ranges. These findings highlight the necessity of model choice suited to data complexity; when concrete exhibits non-linear degradation, ensemble methods such as RF and XGBoost outperform linear or kernel-based alternatives.



(a) (b)

Figure 8. (a) ML Models Prediction and (b) Comparison with Practical Data and RF for M20 Grade



(a) (b)

Figure 9. (a) ML Models Prediction and (b) Comparison with Practical Data and RF for M30 Grade

Moreover, the comparison emphasizes practical implications for structural safety and material design. Predictive models with high accuracy, such as RF, can guide engineers in anticipating material performance under thermal stress, optimizing mix designs, and improving fire resistance and durability of concrete structures. Accurate estimation of compressive strength loss at elevated temperatures is critical for safety assessments, retrofitting, and maintenance planning, particularly in high-rise buildings, tunnels, and industrial structures exposed to fire hazards. Overall, RF emerges as the most physically consistent, statistically robust, and reliable tool for predicting thermal degradation of concrete across multiple grades, offering both theoretical insights and practical utility for civil engineering applications. Performance metrics are shown in Table 5 that indicates RF as the most accurate model, with the highest R^2 and lowest RMSE and MAE for both concrete grades.

Table 2. Performance Metrics of ML Model

Grade	**Parameter**	**LASSO**	**RF**	**XGBOOST**	**SVR**	**Best Model**
	R-Square	0.91384	0.99542	0.98562168	0.94445655	RF
M20	RMSE	1.57334	0.20354	0.36081388	0.70916231	RF
	MAE	1.34014	0.18362	0.32551198	0.53387529	RF
	R-Square	0.98951	0.99573	0.99136358	0.95303196	RF
M30	RMSE	1.61501	0.39239	0.55803894	1.30136405	RF
	MAE	1.59351	0.33854	0.5357492	0.91451071	RF

4 Conclusion

This study explored how elevated temperatures affect the compressive strength of M20 and M30 grade concretes and examined how well different machine learning models can predict this behavior. The results clearly show that concrete strength decreases significantly as temperatures rise, with noticeable degradation occurring beyond 400°C due to internal microstructural damage and cement dehydration. Among the models tested, Random Forest (RF) consistently delivered the most accurate predictions, closely aligning with experimental data and outperforming LASSO, XGBoost, and SVR. Overall, these findings emphasize the vulnerability of concrete to high-temperature exposure and demonstrate the potential of machine learning especially RF as a reliable tool for predicting strength loss, aiding civil engineers in safer structural design and more effective material optimization under thermal stress.

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