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PREDICTING CONCRETE COMPRESSIVE STRENGTH USING LONG SHORT-TERM MEMORY DEEP LEARNING: A DATA-DRIVEN APPROACH FOR ROBUST AND GENERALIZABLE STRENGTH ESTIMATION

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Abstract
Accurate prediction of concrete compressive strength is essential for ensuring structural safety, optimizing mix design, and reducing experimental cost and time. However, the inherent nonlinearity and heterogeneity of concrete materials, particularly when supplementary cementitious materials are involved, limit the effectiveness of traditional empirical and conventional machine learning models. This study proposes a Long Short-Term Memory (LSTM)–based deep learning framework to predict concrete compressive strength using a large and diverse dataset comprising 1,133 samples with varying mix proportions and curing ages. The model incorporates cement, blast-furnace slag, fly ash, water, super-plasticizer, coarse aggregate, fine aggregate, and age of testing as input features. Model performance was rigorously evaluated using training, validation, and test datasets and assessed through multiple statistical and error-based metrics, including R^2, Nash–Sutcliffe Efficiency, RMSE, MAE, MAPE, and CVRMSE. The results indicate strong predictive capability, with R^2 and NSE values consistently exceeding 0.80 across all data partitions, demonstrating effective learning and generalization. Error analysis revealed that prediction errors are largely centred near zero with unimodal distributions, while only minor underestimation was observed for high-strength concrete. Compared with findings reported in recent literature, the proposed LSTM model shows competitive performance and enhanced robustness when applied to a broad strength range and heterogeneous mix designs. The outcomes confirm the suitability of LSTM-based models as reliable tools for preliminary concrete mix design and performance assessment, offering a promising alternative to labor-intensive experimental testing and conventional predictive approaches.

INTRODUCTION

Concrete compressive strength is one of the most critical parameters governing the safety, durability, and serviceability of civil infrastructure, and its accurate prediction remains a longstanding challenge due to the complex, nonlinear interactions among mix constituents, curing conditions, and material heterogeneity. Traditional empirical equations and regression-based approaches, while widely used, often struggle to generalize beyond the experimental conditions for which they were developed, particularly when supplementary cementitious materials, industrial by-products, or advanced mix designs are involved (Hong, 2024; Paudel et al., 2023; Li et al., 2023). As concrete technology evolves toward high-strength, sustainable, and geopolymer-based systems, the limitations of classical modeling techniques have become increasingly evident, motivating the adoption of data-driven and machine learning-based approaches for strength prediction.

In recent years, machine learning (ML) models such as support vector machines, random forests, gradient boosting, and artificial neural networks have demonstrated improved predictive capability compared to conventional methods by capturing nonlinear relationships among input variables (Rathakrishnan et al., 2022; Shaaban et al., 2025; Kalabarige et al., 2024). However, many of these approaches still exhibit sensitivity to hyperparameter selection, overfitting, or reduced accuracy when applied to heterogeneous datasets spanning wide strength ranges or diverse material compositions. Consequently, deep learning architectures, particularly Long Short-Term Memory (LSTM) networks, have attracted growing attention due to their ability to retain and process complex dependencies through gated memory mechanisms (Latif, 2021; Chen et al., 2022).

Although LSTM networks were originally developed for time-series analysis, their capacity to model long-range and nonlinear interactions has proven effective for predicting concrete compressive strength, curing-age-dependent behavior, and performance of geopolymer and cemented sand and gravel systems (Chen et al., 2022; Tian et al., 2023; Gogineni et al., 2023). Recent studies have reported exceptionally high coefficients of determination, often exceeding 0.95, when LSTM models are applied to constrained or specialized datasets such as high-strength concrete or fly ash–slag geopolymer mixes (Chen et al., 2022; Kina et al., 2025). These findings highlight the potential of LSTM-based frameworks to outperform conventional ML techniques such as SVR and RF, particularly in capturing nonlinear strength development mechanisms.

Despite these advances, several research gaps remain. Many existing studies focus on narrowly defined material systems or limited strength ranges, which may overestimate predictive performance and limit real-world applicability (Shi et al., 2024; Kumar et al., 2024). Moreover, comprehensive evaluations using multiple performance metrics, error distribution analysis, and robust training–validation–testing strategies are still lacking in several reported works. Addressing these limitations is essential to establish reliable, generalizable models suitable for engineering practice, especially for preliminary design and performance screening where reducing experimental cost and time is critical (Buddika et al., 2024; Rathakrishnan et al., 2022).

In this context, the present study develops and evaluates an LSTM-based deep learning model for predicting concrete compressive strength using a large and diverse dataset encompassing a wide range of mix proportions, curing ages, and strength levels. By employing rigorous performance assessment, error analysis, and comparison with established benchmarks from the literature, this work aims to demonstrate the robustness and practical applicability of LSTM models for concrete strength prediction while identifying pathways for further improvement through data enrichment and hybrid modeling strategies (Kina et al., 2025; Shi et al., 2024; Imran et al., 2022).

Methodology

Data characteristics

The dataset used in this study comprises 1,133 concrete mix design samples, each characterized by eight input variables and one output variable representing concrete compressive strength. The input parameters include cement content, blast-furnace slag, fly ash, water, super-plasticizer, coarse aggregate, fine aggregate (all measured in kg/m³), and the age of testing in days. The compressive strength, expressed in MPa, serves as the target variable. Descriptive statistical analysis indicates substantial variability across the dataset, reflecting a wide range of concrete mix proportions and curing conditions, which is advantageous for developing a robust predictive model. Cement content varies from 102 to 540 kg/m³, with a mean value of 276.50 kg/m³, highlighting the inclusion of both low- and high-cement mixes. Supplementary cementitious materials show notable dispersion, as blast-furnace slag ranges from 0 to 359.4 kg/m³ and fly ash from 0 to 260 kg/m³, indicating the presence of conventional as well as blended cement concretes. Water content exhibits relatively lower variability, with values ranging between 121.75 and 247 kg/m³, while super-plasticizer dosage varies widely from 0 to 32.2 kg/m³, reflecting different workability requirements. Aggregate contents also demonstrate moderate variation, with coarse aggregate ranging from 708 to 1,145 kg/m³ and fine aggregate from 594 to 992.6 kg/m³. The curing age spans from 1 to 365 days, with a mean of 44.06 days, enabling the model to capture both early-age and long-term strength development. The compressive strength values range from 2.33 to 82.60 MPa, with a mean of 35.84 MPa, covering low- to high-strength concrete categories. Overall, the statistical diversity and scale of the dataset ensure adequate representation of nonlinear relationships among variables, making it well-suited for training and evaluating deep learning models such as LSTM.

Table 1 Descriptive statistical summary of input variables and concrete compressive strength, including count, mean, standard deviation, minimum, quartiles, and maximum values for the 1,133 concrete mix design samples used in this study.

	Cement(kg/m3)	Blast-furnace Slag(kg/m3)	Fly Ash(kg/m3)	Water(kg/m3)	Super-plasticizer(kg/m3)	Coarse Aggregate (kg/m3)	Fine Aggregate (kg/m3)	Age of testing(day)	Concrete compressive strength(MPa)
count	1133	1133	1133	1133	1133	1133	1133	1133	1133
mean	276.504597	74.26624	62.807811	182.984687	6.415538	964.833142	770.490335	44.056487	35.83798
std	103.469947	84.246758	71.583164	21.713923	5.796357	82.788223	79.37387	60.441327	16.100509
min	102	0	0	121.75	0	708	594	1	2.331808
25%	190	0	0	167	0	919	720	14	24.393661
50%	266	26	0	185.7	6.7	966.8	777.5	28	34.673748
75%	342	141.3	121.97	193.8	10.16	1026.6	821	28	44.86834
max	540	359.4	260	247	32.2	1145	992.6	365	82.599225

Figure 1 illustrates the distribution characteristics of the input variables and the target compressive strength using histograms combined with kernel density estimation curves. The cement content distribution exhibits a moderately right-skewed pattern, with most values concentrated between approximately 150 and 350 kg/m³, indicating the predominance of conventional cement dosages while still incorporating higher cement contents for high-strength concrete mixes. In contrast, blast-furnace slag and fly ash show highly skewed distributions with pronounced peaks near zero, reflecting the inclusion of both ordinary Portland cement concretes and blended concretes incorporating supplementary cementitious materials in varying proportions.

The water content distribution appears relatively symmetric and narrowly spread, with a strong concentration around 170–200 kg/m³, suggesting controlled mix designs aimed at achieving consistent workability and strength. Super-plasticizer content demonstrates a distinctly right-skewed distribution, with a large proportion of mixes containing low or zero dosage and fewer samples using higher dosages, which aligns with practical concrete mix optimization strategies. The distributions of coarse and fine aggregates are comparatively normal, centered around approximately 900–1,000 kg/m³ for coarse aggregate and 750–850 kg/m³ for fine aggregate, indicating stable aggregate gradation across most samples.

The age of testing shows a highly non-uniform distribution, with strong clustering at early curing ages, particularly around 7, 14, and 28 days, while fewer samples extend to long-term ages up to 365 days. This imbalance reflects common experimental practices in concrete strength testing. The distribution of concrete compressive strength exhibits an approximately unimodal shape with slight right skewness, spanning from low-strength to high-strength concrete, thereby capturing a broad mechanical performance range. Overall, the observed skewness, multimodality, and nonlinearity across several variables justify the application of advanced deep learning approaches such as LSTM, as linear models may struggle to capture these complex distributional patterns and interactions effectively.

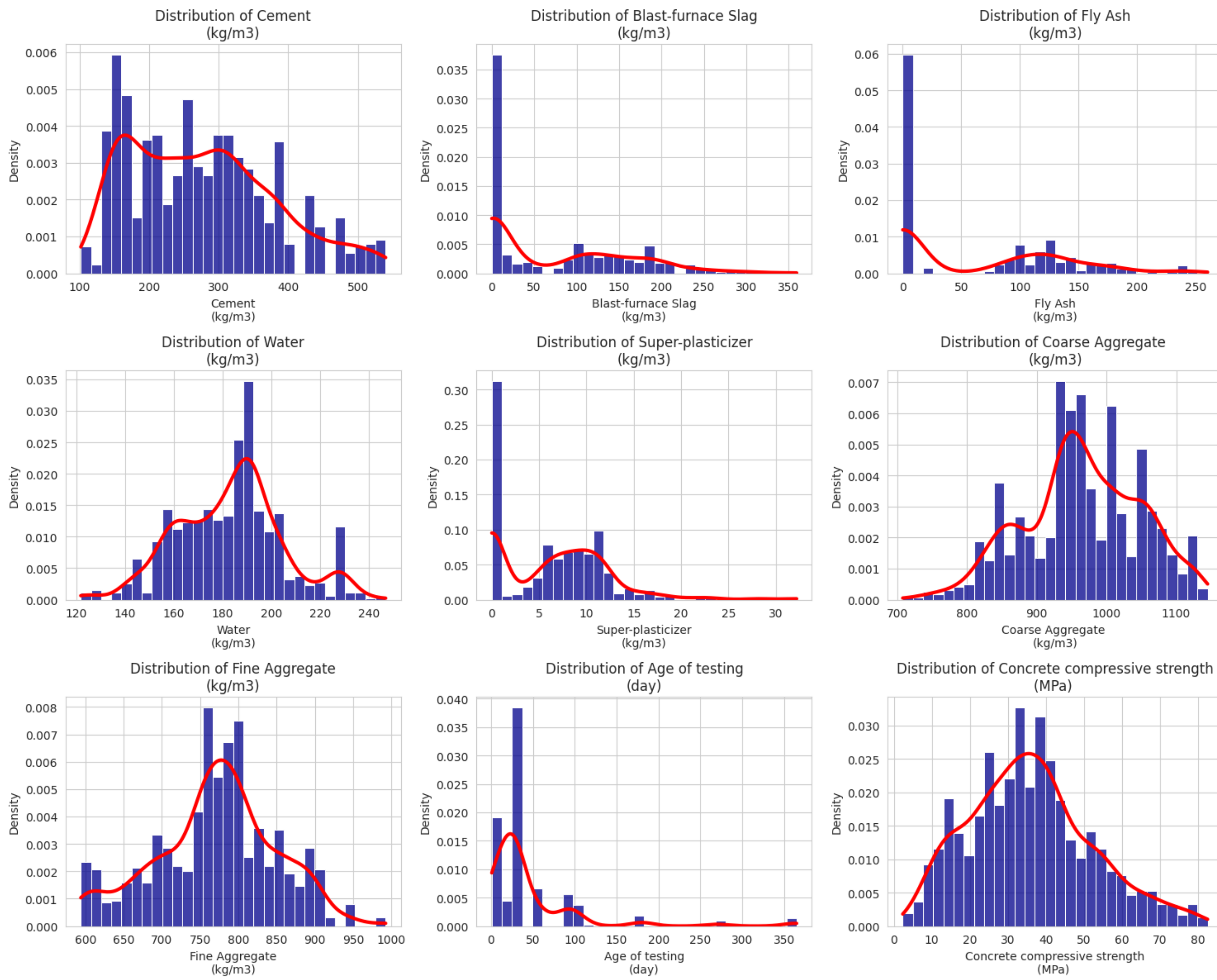
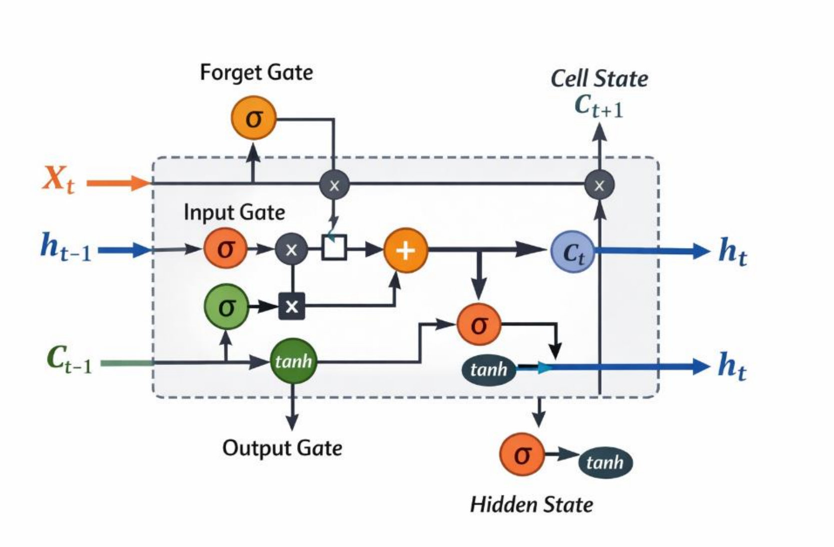


Figure 1 Distribution of input variables and target output in the concrete compressive strength dataset, shown as histograms with overlaid kernel density estimation (KDE) curves, illustrating the statistical spread, skewness, and variability of mix constituents, curing age, and compressive strength.

Model development

In this study, a Long Short-Term Memory (LSTM) neural network was developed to predict the compressive strength of concrete based on mix composition and curing age. Although LSTM networks are traditionally applied to time-series problems, their internal memory mechanism and gated structure enable them to effectively capture complex nonlinear dependencies and long-range relationships among input features, making them suitable for modeling intricate material behavior. Prior to model development, the dataset was preprocessed to ensure numerical stability and learning efficiency. All input variables were normalized using a min–max scaling technique to map values into a uniform range, thereby preventing dominance of features with larger magnitudes. The dataset was then randomly divided into training, validation, and testing subsets to enable model learning, hyperparameter tuning, and unbiased performance evaluation, respectively. The LSTM architecture consists of an input layer corresponding to the eight predictor variables, followed by one or more hidden LSTM layers responsible for learning nonlinear feature interactions through forget, input, and output gates. These gates regulate information flow and mitigate the vanishing gradient problem commonly encountered in traditional recurrent neural networks. A fully connected dense layer was employed at the output stage to generate the final compressive strength prediction. The model was trained using a backpropagation-through-time algorithm, with the Adam optimizer adopted due to its adaptive learning rate and computational efficiency. Mean squared error (MSE) was selected as the loss function to penalize larger prediction errors during training. To prevent overfitting, early stopping was implemented by monitoring validation loss, ensuring optimal generalization performance. Through iterative training and validation, the developed LSTM model learned complex relationships between concrete constituents, curing age, and compressive strength, resulting in accurate and stable predictions across all data subsets.



Model assessment

The performance of the developed LSTM model was evaluated using multiple statistical indicators to comprehensively assess its predictive accuracy, robustness, and generalization capability across the training, validation, and testing datasets. Both goodness-of-fit and error-based metrics were employed to ensure a balanced evaluation of model performance. The coefficient of determination (R^2) was used to quantify the proportion of variance in the observed compressive strength explained by the model predictions. Higher R^2 values indicate stronger agreement between predicted and measured values. Similarly, the Nash–Sutcliffe Efficiency (NSE) was adopted to assess predictive skill relative to the mean of observed data, with values closer to unity representing superior model performance. The consistent use of both R^2 and NSE provides a reliable measure of the model's explanatory power and stability. Error-based metrics were included to evaluate the magnitude and distribution of prediction errors. The Root Mean Square Error (RMSE) emphasizes larger deviations and is particularly sensitive to outliers, making it suitable for assessing overall model accuracy. In contrast, the Mean Absolute Error (MAE) provides a more intuitive measure of average prediction error by treating all deviations equally. The Mean Absolute Percentage Error (MAPE) was used to express prediction accuracy in relative terms, allowing performance comparison across different strength ranges. Additionally, the Coefficient of Variation of RMSE (CVRMSE) was employed to normalize RMSE with respect to the mean observed value, enabling scale-independent assessment.

Results

LSTM

The predictive performance of the proposed LSTM model was evaluated using training, validation, and test datasets, with results summarized through scatter plots of actual versus predicted compressive strength and multiple statistical performance metrics. The close alignment of data points around the 1:1 reference line in all three datasets demonstrates the model's strong predictive capability and consistency across different data splits. This alignment indicates that the LSTM model successfully captures the nonlinear relationships between concrete mix constituents, curing age, and compressive strength.

Quantitatively, the model achieved high coefficients of determination (R^2) of 0.8400, 0.8637, and 0.8057 for the training, validation, and test sets, respectively. These values indicate that more than 80% of the variability in compressive strength is explained by the model, reflecting robust learning and generalization. The Nash–Sutcliffe Efficiency (NSE) values mirror the R^2 results, further confirming the reliability and predictive skill of the model relative to the mean observed strength. Notably, the comparable magnitudes of R^2 and NSE across all datasets suggest that the model does not suffer from significant overfitting.

Error-based metrics further corroborate the model's accuracy. The RMSE values of 6.37 MPa (training), 6.20 MPa (validation), and 7.11 MPa (testing) indicate low overall prediction error, with only a marginal increase in the test dataset. Similarly, the MAE values remain below 6 MPa for all data subsets, demonstrating stable average prediction deviations. The slightly higher errors observed in the test set are expected due to its unseen nature and confirm realistic model performance.

Relative error metrics also show favorable results. The MAPE values of 17.44%, 15.83%, and 19.60% for training, validation, and testing datasets, respectively, indicate acceptable prediction accuracy across a wide strength range. The CVRMSE values remain below 20% for all datasets, further highlighting the model's reliability and consistency. The marginal increase in CVRMSE for the test set reflects minor dispersion in high-strength concrete predictions, which is commonly observed in heterogeneous material datasets.

Table 2 Performance evaluation of the LSTM model for concrete compressive strength prediction across training, validation, and test datasets using statistical and error-based metrics.

Performance Metric	Training Set	Validation Set	Test Set
R-squared (R^2)	0.8400	0.8637	0.8057
Nash–Sutcliffe Efficiency (NSE)	0.8400	0.8637	0.8057
RMSE (MPa)	6.37	6.20	7.11
MAE (MPa)	4.93	4.80	5.57
MAPE (%)	17.44	15.83	19.60
CVRMSE (%)	17.88	17.45	19.06

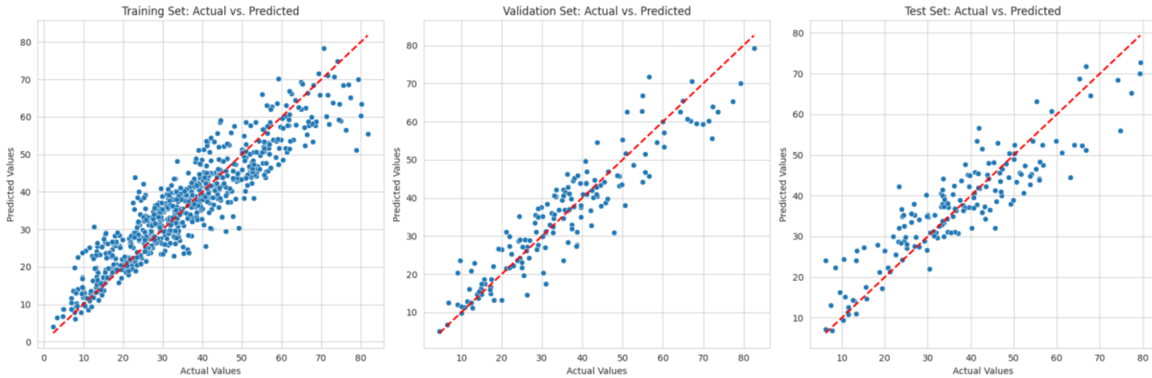


Figure 2 Scatter plots comparing actual and LSTM-predicted concrete compressive strength for the training, validation, and test datasets, with the dashed 1:1 line indicating ideal prediction accuracy.

Error analysis

The predictive reliability of the developed LSTM model was further examined through percentage error distribution analysis for the training, validation, and test datasets. Figure 3 presents histograms of percentage errors overlaid with kernel density curves, providing insight into the magnitude, symmetry, and dispersion of prediction errors across different data subsets.

For the training dataset, the error distribution is approximately unimodal and centered close to zero, indicating minimal systematic bias in model predictions. The majority of errors fall within a narrow percentage range, demonstrating effective learning of underlying data patterns. A slight left-skewness is observed, suggesting occasional overestimation in a limited number of samples, particularly at higher compressive strength values. However, the frequency of extreme errors remains low, indicating controlled variance.

The validation dataset exhibits a similarly concentrated error distribution, with most prediction errors clustered around zero and a marginally broader spread compared to the training set. This behavior reflects good generalization capability and confirms that the model does not overfit the training data. The near-symmetric shape of the validation error distribution further indicates consistent predictive behavior across unseen samples during model tuning.

In the test dataset, the error distribution remains centered near zero but shows a slightly increased spread and mild negative skewness. This behavior is expected due to the presence of previously unseen data and higher variability in material properties. A small number of larger negative percentage errors suggests that the model tends to underestimate compressive strength in certain high-strength or long-curing-age concrete samples. Nevertheless, the dominant concentration of errors within acceptable bounds demonstrates stable performance.

Overall, the narrow error distributions and strong central tendency across all datasets confirm the robustness and reliability of the LSTM model. The absence of pronounced multimodality or heavy-tailed distributions indicates effective learning of nonlinear relationships without excessive sensitivity to outliers. These findings complement the statistical performance metrics and further validate the suitability of the proposed LSTM approach for accurate concrete compressive strength prediction.

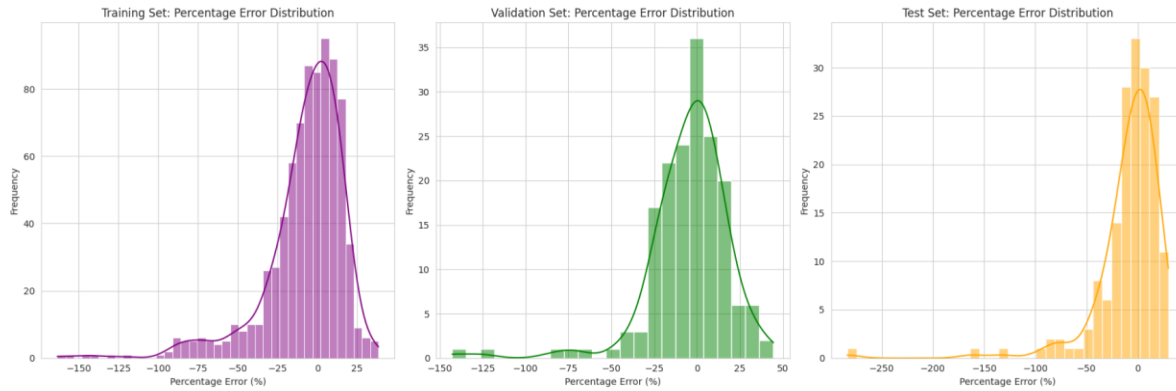


Figure 3 Percentage error distributions of LSTM-predicted concrete compressive strength for the training, validation, and test datasets, illustrating the spread, symmetry, and bias of prediction errors.

Discussion

The strong predictive performance of the developed LSTM model, as reflected by R^2 and NSE values consistently above 0.80 for the training, validation, and test sets, indicates that the network captures most of the variability in compressive strength while maintaining good generalization. This level of accuracy aligns with the growing body of evidence that LSTM-based architectures are well suited to modeling the complex, nonlinear relationships between mix proportions, curing age, and strength in cementitious and geopolymer systems (Chen et al., 2022; Latif, 2021; Tian et al., 2023; Gogineni et al., 2023; Kina et al., 2025). For instance, LSTM models for high-strength concrete, conventional concrete, and CSG have reported coefficients of determination above 0.97–0.99 with low RMSE and MAE, outperforming traditional machine learning techniques such as SVR, RF, and SVM (Chen et al., 2022; Latif, 2021; Tian et al., 2023; Gogineni et al., 2023). Although the absolute error levels in the present study are somewhat higher, likely reflecting a broader strength range, heterogeneous materials, or more diverse mix designs, the R^2 and NSE values above 0.80 still fall within the range considered satisfactory for engineering prediction tasks (Kina et al., 2025; Shi et al., 2024; Rathakrishnan et al., 2022).

The relatively close agreement among the training, validation, and testing statistics supports the assertion that the model does not substantially overfit the training data. This is consistent with other LSTM-based concrete strength studies where training–testing performance gaps were modest and error distributions remained compact and approximately normal (Chen et al., 2022; Kina et al., 2025; Tian et al., 2023; Shi et al., 2024). The RMSE of about 6–7 MPa and MAE under 6 MPa in all data partitions, combined with MAPE values between roughly 15–20%, suggest that the model yields practically acceptable predictions over a wide compressive strength spectrum. Comparable or even lower error levels have been reported in optimized LSTM or CNN–LSTM frameworks, but often on more constrained datasets in terms of materials or strength range (Chen et al., 2022; Kina et al., 2025; Shi et al., 2024; Imran et al., 2022). In contrast, classical models such as linear regression or weaker ensemble/ML baselines commonly show higher RMSE and MAPE and greater scatter for high-strength data (Hong, 2024; Shaaban et al., 2025; Paudel et al., 2023; Li et al., 2023).

The analysis of relative error metrics (MAPE, CVRMSE) and error distributions provides additional insight into model robustness. MAPE values under 20% and CVRMSE under 20% across all subsets indicate that the LSTM delivers stable relative accuracy, in line with other studies where well-tuned deep or ensemble models achieve similarly low relative errors and tight confidence bands (Kina et al., 2025; Shi et al., 2024; Rathakrishnan et al., 2022; Kalabarige et al., 2024). The histograms of percentage errors centered near zero, with unimodal and near-normal shapes for all partitions, mirror the behavior observed in other high-performing models for geopolymer and high-strength concretes, where most samples fall within ±20% error and extreme outliers are rare (Kina et al., 2025; Shi et al., 2024; Paudel et al., 2023). The slight negative skewness and modest widening of the error distribution in the test set, especially for higher-strength or long-age specimens, are also consistent with reported tendencies of many models to underpredict at the upper strength tail, where microstructural heterogeneity and data scarcity make learning more difficult (Kina et al., 2025; Kumar et al., 2024; Shaaban et al., 2025; Han et al., 2022).

From an application standpoint, these characteristics imply that the proposed LSTM model can be used as a reliable tool for preliminary design and performance screening, helping to reduce the number of laboratory trials and accelerate mix optimization. Similar conclusions have been drawn where LSTM or optimized LSTM variants were recommended for pre-estimation of compressive strength before destructive testing, particularly in high-strength or eco-concrete systems using industrial by-products (Chen et al., 2022; Latif, 2021; Buddika et al., 2024; Shi et al., 2024). At the same time, the residual underestimation at higher strengths, as noted in the error analysis, suggests potential benefits from targeted data augmentation in the upper strength range, incorporation of additional microstructural or curing-related features, or hybridization with optimization or ensemble techniques, as demonstrated in LSTM–MPA and CNN–LSTM frameworks (Gali et al., 2023; Mujtaba et al., 2023; Shah et al., 2023; Khan et al., 2025; Nawaz et al., 2025, Shi et al., 2024; Imran et al., 2022). Addressing these aspects could further narrow prediction errors, enhance reliability for critical structural applications, and bring the performance of the present model closer to the best-performing deep learning and boosting-based approaches reported in recent literature (Kina et al., 2025; Shi et al., 2024; Rathakrishnan et al., 2022; Kalabarige et al., 2024).

Conclusion and recommendation

This study presented the development and comprehensive evaluation of a Long Short-Term Memory (LSTM)–based deep learning model for predicting the compressive strength of concrete using a large and diverse dataset encompassing a wide range of mix proportions, curing ages, and strength levels. The results demonstrated that the proposed model is capable of accurately capturing the complex, nonlinear relationships between constituent materials, curing time, and compressive strength, as reflected by consistently high R^2 and Nash–Sutcliffe Efficiency values exceeding 0.80 across training, validation, and test datasets. The close agreement between predicted and observed values, together with relatively low RMSE and MAE and acceptable relative error measures (MAPE and CVRMSE), confirms the robustness and generalization capability of the LSTM model and indicates that overfitting was effectively controlled. Error distribution analysis further revealed that prediction errors are largely centered near zero and exhibit unimodal, near-normal behavior, with only limited skewness in the test set, primarily at higher strength levels where material heterogeneity and data scarcity typically pose greater challenges. These findings are consistent with and supportive of recent literature demonstrating the superiority of LSTM-based frameworks over traditional regression and conventional machine learning models for concrete strength prediction, particularly when dealing with nonlinear and high-dimensional input spaces. From a practical standpoint, the developed model offers significant potential as a reliable decision-support tool for preliminary mix design, performance screening, and optimization, enabling practitioners to reduce the number of costly and time-consuming laboratory trials while maintaining acceptable prediction accuracy for engineering applications. At the same time, the observed tendency toward slight underestimation in the upper strength range suggests avenues for future enhancement, including targeted data augmentation for high-strength mixes, incorporation of additional explanatory variables related to microstructure, curing conditions, or environmental exposure, and the integration of hybrid or ensemble strategies such as LSTM–CNN or LSTM combined with metaheuristic optimization. Further validation using independent experimental datasets and extension to specialized concrete systems, including ultra-high-performance, geopolymer, and recycled aggregate concretes, would also strengthen confidence in real-world deployment. Overall, the outcomes of this study confirm the effectiveness and practical relevance of LSTM models for concrete compressive strength prediction and provide a solid foundation for future research aimed at advancing data-driven approaches in sustainable and high-performance concrete design.

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