Using Deep Learning for Profitable Concrete Forecasting Methods

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Abstract: *In contemporary construction practices, the precision in forecasting the efficacy of concrete infrastructures plays a pivotal role in ensuring both economic viability and structural robustness. Classical methodologies often falter in encapsulating the myriad variables that intricately govern concrete performance, underscoring the exigency for progressive predictive apparatuses. This manuscript endeavors to fill this lacuna by harnessing a diverse spectrum of computational algorithms, namely linear regression, Gated Recurrent Units (GRU), Long Short-Term Memory (LSTM), and WaveNet, and subjecting them to scrupulous evaluation across multifarious metrics to discern their inherent capabilities and constraints of paramount significance, WaveNet manifested commendable prowess, registering an R^2 coefficient of 0.884 and a Root Mean Square Error (RMSE) of 23.22. Complementing the technical assessment, this study infuses an economic perspective, elucidating a cogent cost-efficiency rationale advocating the ubiquitous integration of these avant-garde predictive modalities within the construction milieu. Our interdisciplinary stratagem forges a novel conduit for synergetic research, intertwining the realms of civil engineering, computational analytics, and fiscal studies. The empirical results accentuate that machine learning paradigms not only augment predictive precision but also bolster economic viability, heralding them as indispensable instruments in the avant-garde toolkit of construction administration.*

Keywords: *Concrete performance prediction, machine learning, deep learning, construction management, regression.*

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1. Introduction

In the context of the evolving complexity of modern construction practices, the twin challenges of ensuring durability and economic sustainability are increasingly prominent. Conventional methodologies, including manual inspections and basic statistical models, are proving insufficient for a comprehensive understanding of the intricate interplay among environmental factors, mechanical stresses, and material characteristics that affect the structural integrity of concrete [16]. This necessitates more advanced, accurate, and cost-efficient methods for forecasting. Our study addresses this gap by adopting Deep Learning algorithms [15], a departure from traditional analytical approaches.

Machine Learning (ML) [5, 17], and Deep Learning (DL) [13, 21] are both subsets from Artificial Intelligence (AI), where ML simply can be defined as a statistical tools used to explore and analyze the data. There exist three types of ML techniques called Supervised, Unsupervised, and semi Supervised. However, DL use Multi- Neural networks architectures. There exist three kinds of neural networks called Artificial Neural Networks (ANN), Convolutional Neural Network (CNN), and Recurrent Neural Network (RNN).

The impetus for this research derives from the acknowledgment that machine learning advancements, particularly in deep learning, provide unparalleled opportunities for predictive modeling. These models incorporate a vast array of variables impacting concrete performance [14], allowing predictions not only about potential structural failures but also about optimizing construction materials for better durability. Additionally, this study incorporates an economic perspective, often neglected in academic contexts but vital for practical application, by evaluating the potential cost savings through optimized maintenance and material use.

This research represents a confluence of civil engineering, materials science, and artificial intelligence, potentially transforming the way we understand and maintain one of the most crucial building materials [15]. The primary aim is to advance Concrete Strength (CS) forecasting by utilizing various computational models, including linear regression [22], Gated Recurrent Units (GRU) [25], Long Short-Term Memory (LSTM) [16], and WaveNet [24]. This blend of traditional statistical methods and advanced machine learning aims to yield more accurate, reliable, and economically viable predictive models.

Linear regression will establish a foundational understanding of the linear correlations in our dataset. The inclusion of GRU and LSTM, both recurrent neural network variants, addresses the temporal dynamics often overlooked by conventional engineering models. WaveNet, originally designed for audio signal

processing, will help explore the complex, non-linear relationships in our dataset.

A thorough comparative analysis of these models is planned to evaluate their effectiveness in predicting CS, service life, and key mechanical properties. This study also seeks to determine how these models perform across different types of data, such as time-series for aging analysis and cross-sectional data for mechanical characteristics. The end goal is to integrate these insights into a comprehensive forecasting tool that is both technically precise and economically viable. This holistic approach not only aims to improve predictive accuracy but also assesses the practicality and profitability of implementing these sophisticated algorithms in real-world construction scenarios.

The main contributions in this paper can be summarized as illustrated here, as a first contribution, this study presents a groundbreaking integration of conventional engineering techniques with advanced computational models, addressing the critical issue of forecasting concrete performance. Firstly, it stands as one of the initial comprehensive investigations to utilize a variety of machine learning models-namely, linear regression, GRU, LSTM, and WaveNet-for assessing CS, its mechanical attributes, and longevity [22]. This diversified multi-model strategy not only enhances the accuracy and dependability of forecasts but also deepens the understanding of the intricacies associated with concrete deterioration.

Secondly, through an exhaustive comparative analysis, our research contributes a valuable framework for both scholars and industry professionals. This framework aids in selecting the most suitable model based on the nature of the data, the objectives of the prediction, and available computational resources. This contribution is particularly significant in light of the limited comparative analyses available in current literature.

Thirdly, our study introduces an economic dimension to the conversation about predictive modeling in the realm of construction management. It articulates a comprehensive cost-benefit analysis, underscoring the economic viability and practical benefits of adopting machine learning approaches for forecasting. This aspect argues persuasively for their broader implementation within the industry.

Fourthly, the interdisciplinary approach of our work serves to bridge the existing divides among civil engineering, data science, and economics. This fusion not only fosters a more comprehensive understanding but also encourages interdisciplinary collaboration for future explorations.

Finally, the scalability and versatility of the predictive models we have developed extend their utility beyond concrete analysis. They could potentially serve as a blueprint for projecting the performance of other building materials and systems, marking a significant advancement in the field.

The rest of this paper is organized as follows section 2 displays the most recent studies conducting on using ML, and DL techniques for forecasting concrete. The methodology has been demonstrated in section 3. In section 4, the experimental setups are displayed while section 5 is devoted to presenting and discussing the results. Finally, section 6 draws the conclusion.

2. Literature Review

From one hand, this section will provide a comprehensive analysis of the most recent works in the literature related to using ML, and DL techniques for forecasting concrete. On the other hand, the Limitations and gaps in the previous related works will be discussed in this section for demonstrating the main contributions in this paper.

2.1. Machine Learning Techniques for Forecasting Concrete

Within the ambit of concrete technology research, a series of studies have progressively employed advanced machine learning methodologies to enhance the precision in predicting CS and to elucidate the key factors influencing its characteristics. The investigation delineated Ahmad *et al*. [1] incorporated decision tree algorithms, bagging regressors, and AdaBoost regressors for the prognostication of CS in fly ash-based geopolymer concrete. Among these, the bagging model demonstrated a superior predictive capability, evidenced by an R-squared value of 0.97. Additionally, a comprehensive sensitivity analysis was executed to identify salient parameters impacting CS, concurrently accentuating the environmental sustainability of geopolymer concrete.

Concurrently, the inquiry presented by Feng *et al*. [12] innovated an AdaBoost-based intelligent methodology for CS estimation. With an extensive dataset encompassing 1030 test sets, this approach outperformed traditional machine learning frameworks such as ANN and Support Vector Machines (SVMs), a finding substantiated through rigorous 10-fold cross-validation procedures and sensitivity analyses.

Directing attention towards Recycled Aggregate Concrete (RAC), the study by Ahmad *et al*. [3] leveraged symbolic learning approaches, specifically Gene Expression Programming (GEP) and ANNs, to evaluate CS. The GEP method exhibited superior efficacy compared to ANNs, with the employment of sensitivity analysis further aiding in the identification of influential parameters. This study also underscored the potential enhancement in prediction accuracy through the integration of boosting and bagging techniques.

Focusing on the shear resistance of Steel Fiber-Reinforced Concrete (SFRC) beams, Rahman *et al*. [20] deployed various machine-learning models, with the XGBoost algorithm emerging as the most accurate. This

study underscored the importance of certain input features in predicting the shear strength of SFRC beams, thereby offering deeper insights into material behavior under stress.

Addressing the prediction of bond resistance between concrete and Fiber Reinforced Polymer (FRP), the study by Chen *et al*. [7] employed the Gradient Boosting Regression Trees (GBRT) approach. Using a comprehensive database of 520 samples, the GBRT model was noted for its exceptional accuracy and reliability, outperforming other models in this domain.

Wang *et al.* [27], a unique combination of ANNs with Genetic Algorithms (GAs) or Particle Swarm Optimization (PSO) was proposed for bond strength prediction in Composite Engineered Steel (CES) constructions. The PSO-ANN model was notably efficacious, surpassing traditional models and empirical equations, with a detailed sensitivity analysis isolating significant variables affecting bond strength.

Ahmed *et al*. [4] investigated the applicability of machine learning models, including AdaBoost, random forests, and decision trees, for CS prediction at elevated temperatures. The AdaBoost algorithm was identified as the most effective, as evidenced by a high R-squared value and minimal root mean square residual sensitivity analysis in this study highlighted cement content as a pivotal factor.

Dao *et al*. [9], in the study scrutinized the efficacy of Gaussian Process Regression (GPR) and ANNs in forecasting the CS of High-Performance Concrete (HPC). GPR, particularly with the Matern32 kernel function, was identified as superior, with cement concentration and testing age as critical determinants through sensitivity analysis.

In Derousseau *et al*. [11], ML methods, notably random forest, were applied to CS prediction utilizing a blend of laboratory and field data. The model trained on field data was notably more accurate, suggesting the effectiveness of combining diverse data sources to mitigate over-prediction in modeling.

Amin *et al*. [6] employed decision tree and gradient boosting tree models to evaluate the flexural capacity of FRP-reinforced concrete beams. Here, the gradient boosting tree model demonstrated superior performance, with the study utilizing diverse evaluation metrics and identifying beam depth and flexural reinforcement area as key influencing factors.

Song *et al*. [23] compared four machine-learning techniques: Gene expression programming, artificial neural networks, decision trees, and bagging, in the context of CS prediction. The Bagging technique was identified as the most accurate, marked by an R-squared value of 0.95.

In Wan *et al*. [26], the focus was on estimating CS based on concrete composition and curing period, where the XGBoost model with manually selected features showed outstanding effectiveness. The study also revealed the benefits of dimensionality reduction, particularly for the support vector regression model.

The investigation in Oey *et al*. [18] examined the prediction of setting time and strength development in ordinary port and cement binders using machine-learning techniques, concluding that these methods can yield predictions on par with traditional ASTM test methods.

Finally, the exploration by Ahmad *et al*. [2] assessed the utility of ensemble machine learning techniques like ANN, boosting, and AdaBoost for the CS prediction of high-calcium fly ash-based geopolymer concrete. The boosting method was distinguished for its precision, emphasizing the potential of ensemble methods in enhancing concrete composition for sustainable development.

2.2. Limitations of Existing Methods

The current landscape of CS prediction methodologies, while having made substantial progress, confronts certain intrinsic limitations, particularly in the context of traditional machine learning models such as SVM [12], decision trees, and random forests [11]. These limitations primarily stem from their inherent characteristics and the nature of concrete behavior analysis.

Firstly, these traditional machine-learning models often exhibit limitations in comprehensively capturing the intricate and non-linear interdependencies, as well as the time-dependent variables inherent in concrete's behavior throughout its service life. Concrete, as a material, exhibits complex properties that evolve over time, influenced by a multitude of factors such as environmental conditions, aging, and material composition. The linear and somewhat static modeling approach of traditional machine learning methods may not fully encapsulate these dynamic interactions and changes, thereby potentially leading to less accurate predictions over the long term.

Additionally, these models generally necessitate extensive feature engineering and meticulous hyperparameter tuning. Such processes are not only time-intensive but also heavily rely on domain-specific knowledge, which could pose a barrier to practitioners who may lack such specialized expertise. This requirement for detailed upfront configuration and tuning could hinder the adaptability of these models to novel or varied datasets. Consequently, their application might be confined to specific scenarios or data distributions, limiting their broader utility in diverse CS prediction contexts.

Moreover, a significant drawback of traditional machine learning models is their lack of capability to autonomously learn and identify feature representations [10]. This is in contrast to deep learning models, which have the intrinsic ability to unearth complex patterns and relationships within data that might not be immediately discernable through conventional

analytical techniques. The absence of this advanced feature learning capability in traditional models might lead to oversight of potentially crucial insights hidden within the data.

In light of these constraints, it becomes apparent that the journey towards enhancing the accuracy and reliability of CS predictions using solely traditional machine learning models may be approaching a saturation point. This realization underscores the need for venturing into more sophisticated computational methodologies. Exploring and integrating advanced approaches, particularly those stemming from the realm of deep learning and other emergent AI technologies, could offer significant breakthroughs in understanding and predicting concrete behavior more accurately and comprehensively. This shift towards embracing more advanced computational paradigms could mark the next frontier in the evolution of CS prediction methodologies.

2.3. Deep Learning Techniques for Forecasting Concrete

The realm of CS prediction has been witnessing a transformative shift with the integration of deep learning and traditional machine learning techniques. This synthesis is evident in recent research efforts that aim to enhance prediction accuracy and reliability by harnessing the strengths of both methodologies.

In research work identified by Latif *et al*. [16], a novel approach combining LSTM, a deep learning technique, with SVM, a traditional machine-learning algorithm, was explored. This hybrid model was applied to predict the compressive strength of High-Performance Concrete (HPC), utilizing a comprehensive dataset derived from prior studies. The performance evaluation, conducted using a variety of metrics, revealed the superior capability of the LSTM model over SVM in forecasting the compressive strength of HPC, highlighting the potential of LSTM as an effective tool for strength estimation in such concrete types.

In another significant study, Zeng *et al*. [28] focused on the development of a deep-learning model specifically designed to predict the 28-day compressive strength of concrete. This study critiqued traditional models for their reliance on "unexplainable features" and proposed a novel "factors-to-strength" methodology. This approach utilized "explainable features" like the water-to-binder ratio and sand-to-aggregate ratio, aligning more closely with the practical knowledge and experience of concrete engineers. Trained on a dataset comprising 380 groups of concrete mix variations, the model's validation against other prevalent models such as SVM, ANN, and AdaBoost demonstrated its high accuracy and superior generalization capability, as indicated by its impressive coefficients of determination.

The research conducted by Caihua *et al*. [19], undertook the task of evaluating the effectiveness of three Artificial Intelligences models-Adaptive Neuro-Fuzzy Inference System (ANFIS), Multi-Layer Perceptron (MLP), and Radial Basis Function (RBF) in predicting concrete slump. Employing seven input parameters, the study rigorously assessed these models using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The findings positioned ANFIS as the most proficient model in both the training and testing phases, outperforming MLP and RBF, and thereby underscoring its potential application in concrete slump prediction.

Lastly, in the study marked by Haque *et al*. [14], the research delved into predicting the compressive strength of Magnesium Phosphate Cement (MPC) composites. This investigation was characterized by the development and evaluation of innovative hybrid models that meld deep learning with traditional machine learning techniques. Utilizing data from existing literature and employing a 70-30 split for training and testing, the study developed four hybrid models-CNN-LSTM, CNN-GRU, DTR-RFR, and GBR-RFR. These models, particularly CNN-LSTM and GBR-RFR, demonstrated high accuracy in their predictions. Additionally, the application of the SHAP algorithm provided insights into the key input variables and the predictive processes of these models, suggesting their applicability and usefulness in real-world construction scenarios.

These studies collectively signify a burgeoning trend in CS prediction-a movement towards integrating the nuanced capabilities of deep learning with the established frameworks of traditional machine learning, aiming to yield more accurate, reliable, and contextually relevant predictive models.

2.4. Gaps in the Deep Learning Research that this Paper Aims to Fill

The current landscape of research in CS prediction and quality assessment has seen significant strides with the application of machine learning techniques. However, there's a discernible research gap in the utilization of specialized deep learning models tailored for this field. Predominantly, the focus has been on traditional machine learning models like SVM, ANFIS, and MLP. These models, though effective to a degree, might not fully encapsulate the advanced pattern recognition and data abstraction capacities that are hallmark features of deep learning algorithms.

Recent literature has touched upon hybrid models that merge deep learning with traditional machine learning, yet such instances remain relatively sparse in the domain of concrete material science. This opens up a substantial research opportunity to delve into and critically evaluate the potential of deep learning architectures, specifically GRU, LSTM, and Wavenet.

These architectures are especially proficient in capturing temporal dependencies and complex nonlinear interactions, which are crucial for accurately deciphering and forecasting the dynamic properties of concrete compositions across various conditions and over time.

In response to this gap, our forthcoming research endeavors to develop and meticulously assess models founded on GRU, LSTM, and Wavenet algorithms. Our objective is to conduct a comprehensive comparative study. This study aims not only to measure the performance of these deep learning architectures in relation to each other but also to examine their effectiveness compared to the existing traditional and hybrid models.

Such an investigative approach is poised to infuse new insights into the scientific discourse on concrete material prediction. This, in turn, holds the promise of greatly benefitting the community of construction engineering and material science researchers and practitioners. By leveraging the nuanced capabilities of these deep learning models, we aspire to foster a more profound and nuanced understanding of concrete behavior, which is pivotal for advancing the field and enhancing practical applications in construction and material engineering.

3. Methodology

In the proposed work we meticulously adopt a structured five-phase methodology that guarantees detailed data analysis and robust model development for predicting CS in construction projects, particularly focusing on British Columbia. The initial phase is Data Collection, where we accumulate a comprehensive dataset that is pivotal for CS forecasting. This dataset serves as the foundation of our study, encompassing various parameters relevant to the construction industry.

Subsequent to data acquisition, our second phase is Exploratory Data Analysis (EDA). During this phase, a thorough examination of the dataset is conducted. This includes scrutinizing the data structure, pinpointing anomalies or outliers, and acquiring a holistic understanding of the dataset's intrinsic characteristics. EDA is instrumental in unveiling underlying patterns and potential inconsistencies in the data, thereby guiding the subsequent processing stages.

The third phase, data preprocessing, is dedicated to refining the dataset. This involves meticulous data cleaning and normalization or scaling of features. Such preprocessing is crucial as it directly influences the efficacy of the machine learning algorithms applied later. By normalizing the data, we ensure that the models are not biased or skewed by the scale of the input features, allowing for a more accurate and generalizable model performance.

Our fourth phase, the heart of our methodology, is the Modeling phase. In this stage, a diverse array of models is deployed, including but not limited to linear regression, LSTM, GRU, and WaveNet. The selection of these models is strategically made to encompass a range of complexities and patterns present in the data. This diversity in modeling techniques is essential for a comprehensive and nuanced analysis of the predictive capabilities across various model architectures.

Finally, the Evaluation phase marks the culmination of our research process as shown in Figure 1. In this phase, the performance of each model is meticulously assessed using an array of statistical metrics such as RMSE, Coefficient of Determination (R2), and MAE. These metrics provide a multifaceted view of the models' accuracy, reliability, and applicability in real-world scenarios. The systematic application of this methodology ensures that our research maintains high standards of accuracy and reliability in forecasting CS, thereby contributing valuable insights to the field of construction engineering.

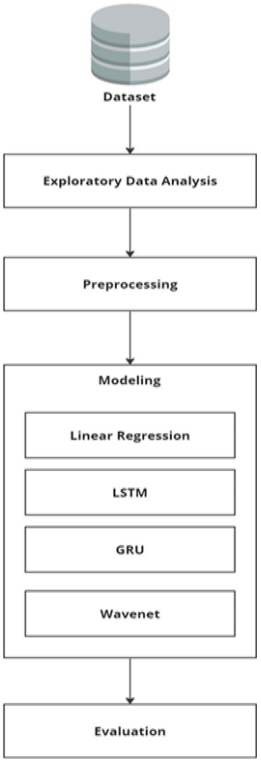

Figure 1. Proposed approach.

3.1. Dataset

The dataset frequently used for predicting CS stands as a prominent resource within the machine learning and data science landscape, particularly within the purview of construction research. This dataset encompasses 1030 entries, with each sample epitomizing a unique concrete mixture, differentiated by 9 salient attributes. The fundamental aim of harnessing this dataset is to deduce the compressive strength of the varied concrete mixtures, considering the given attributes. Such prognosticative insights are of paramount importance to industry practitioners, especially engineers and architects, as they often grapple with the need for precise strength metrics for their infrastructural endeavors [8].

This dataset, widely available to the public, has been referenced extensively in scholarly discourses and papers, underscoring its robustness and reliability for stakeholders in construction-centric research or applications. In a graphical representation delineated as Figure 2, the distribution of our focal variable CS is portrayed. This histogram, partitioned into 20 distinct bins, aligns the strength metrics on the x-axis while cataloging their respective frequencies on the y-axis, offering a comprehensive overview of strength dispersion within the dataset.

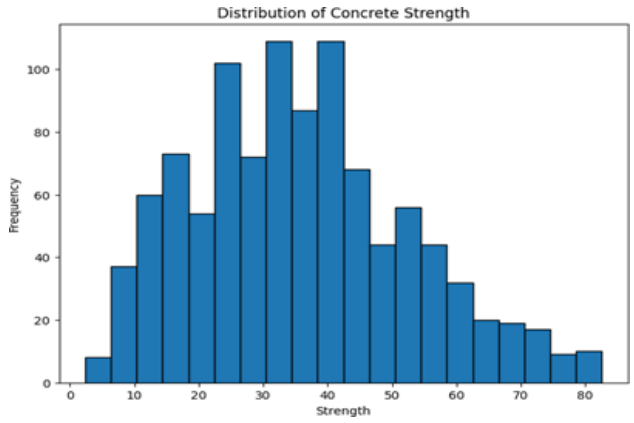

Figure 2. Distribution of CS.

3.2. Exploratory Data Analysis (EDA)

Figure 3 showcases a correlation heatmap, an illustrative tool that elucidates the interrelations among different attributes within the dataset. This visualization is particularly insightful, revealing the absence of high correlations among the features. Such a scenario indicates that multicollinearity a statistical phenomenon where predictor variables in a regression model are highly correlated does not pose a significant issue in this dataset. This aspect is vital for ensuring both the robustness and the interpretability of any machine learning models that are trained on this data.

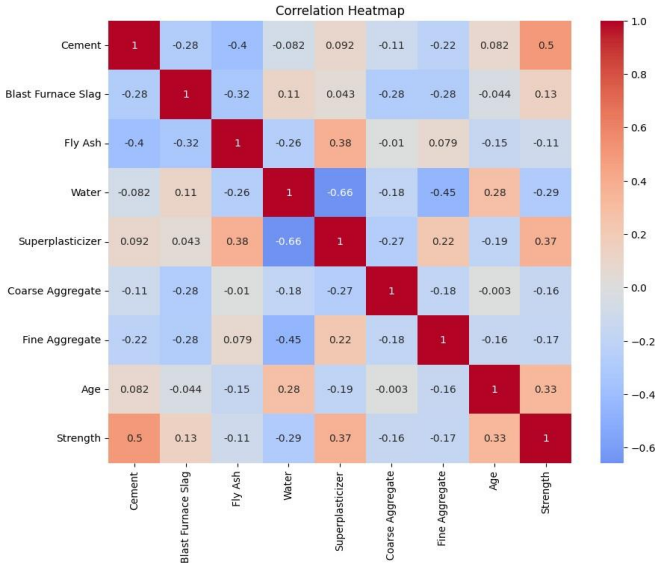

Figure 3. Correlation heatmap between features.

Figure 4 features an array of box plots, each corresponding to a different feature in the dataset. These plots serve as a comprehensive graphical method to display the distribution, central tendency, and variability of the data. Central to each box plot is the median of the data, which divides the data set into two halves. The edges of the box indicate the first and third quartiles, effectively capturing the interquartile range and offering a glimpse into the spread of the central 50% of the data.

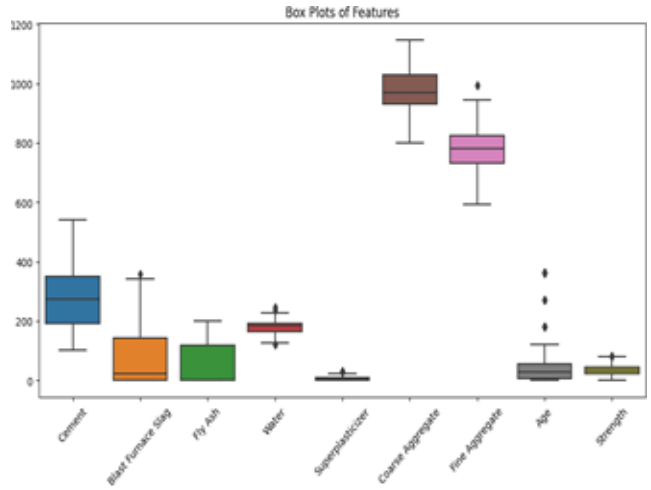

Figure 4. Box plots for each feature.

Additionally, the box plots provide insights into potential outliers, represented by points outside the typical range of the data. These outliers can be critical in understanding anomalies or unique characteristics within the dataset. The whiskers of the box plots extend to show the range of the data, except for these outliers. The presence or absence of skewness in the data can also be visually assessed through these plots, making them a valuable tool for preliminary data analysis. This feature-by-feature graphical summary, therefore, allows for a quick and effective assessment of the key statistical properties of each variable in the dataset.

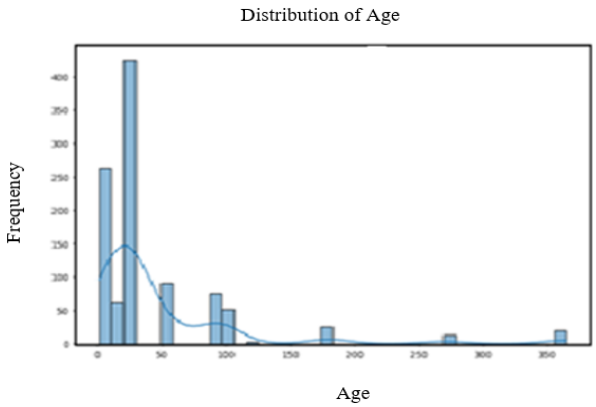

Figure 5. Distribution of the age.

The histogram represented in Figure 5 complemented by the Kernel Density Estimate (KDE), offers an insightful portrayal of the ‘Age’ feature's distribution. Spanning from day 1 to day 365, the age of the samples

seems to be skewed towards the younger spectrum. A striking concentration of data points is evident around the early stages, with the highest frequency being in the category below 50 days. This observation implies that a substantial portion of the concrete mixtures examined are relatively fresh, with fewer samples having an age that extends into the later part of the range.

Further amplifying this observation, the KDE curve representing the data's probability density peaks prominently at the earlier stages, underlining the preponderance of younger samples. As we move towards the higher age values, both the histogram and the KDE curve wane, confirming a decline in the frequency of older samples. This pronounced emphasis on younger ages highlights the dataset's inclination towards samples in their early stages of curing or setting. Such insights can be instrumental for researchers and practitioners, as understanding age distribution can influence the interpretation of other features and the generalizability of resulting models.

3.3. Preprocessing

In our research, the task of partitioning the dataset was accomplished utilizing the train_test_split function from the renowned scikit-learn library. This was a deliberate move to segregate the dataset into distinct training and testing subsets, which we designated as X_train and X_test respectively, alongside their corresponding y_train and y_test labels. The underlying motivation was to ensure our developed model's capacity to generalize to novel data. As a benchmark, we allocated a substantial 80% of the entire dataset to training, reserving the remaining 20% solely for testing purposes. This proportionate split was achieved by setting the test size parameter to 0.20.

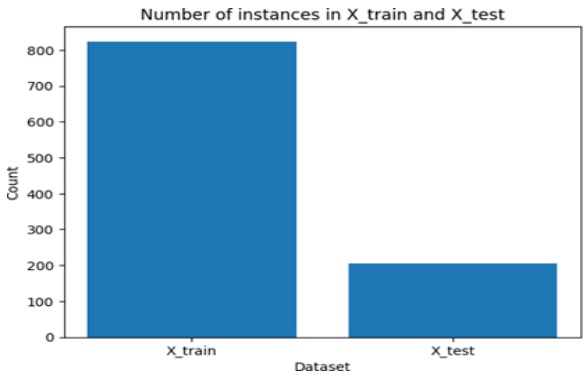

Figure 6. Training and test sets distribution.

To uphold the data's integrity and prevent inadvertent biases, the shuffle parameter was set to True, ensuring a randomized distribution of the data. Additionally, to instill reproducibility in our experiments, we anchored the random state parameter to 0. This ensures that identical data splits are achieved consistently, regardless of the number of iterations or runs. Leveraging this tailored data segregation, our machine learning classifier underwent rigorous training and subsequent evaluation. Figure 6 graphically delineates the division, portraying the count distribution between the training and test datasets.

To set the stage for the training of our advanced deep learning algorithms, we employed standardization as our preferred technique for feature scaling during the data preprocessing phase. This approach, revered in both machine learning and deep learning paradigms, ensures that each feature in the dataset conforms to a consistent range and distribution. This uniformity greatly amplifies the model's receptiveness to variations within the input data.

The potency of standardization becomes more evident when considering its capacity to expedite the convergence of optimization routines intrinsic to deep learning architectures. To actualize this standardization, each feature was recalibrated to exhibit a zero mean and a variance of one. This was achieved by deducting the mean and subsequently dividing by the respective standard deviation for every individual attribute. Such a transformation not only harmonizes the data spectrum but also bolsters the efficiency and robustness of the machine learning models harnessed in our investigation.

3.4. Model Evaluation Metrics

This section delves into the regression metrics employed to gauge the performance of models designed for continuous prediction, as corroborated by established scholarly works.

3.4.1. Root Mean Square Error (RMSE)

RMSE is a widely recognized metric in machine learning for gauging the performance of regression models.

It calculates the square root of the average squared differences between actual and predicted values, serving as a gauge of the model’s predictive accuracy.

Lower RMSE scores indicate improved predictive capabilities for continuous variables, such as property prices, stock market indices, or climatic variables.

Fundamentally, RMSE provides valuable insights into the extent of errors in model predictions, making it a vital measure of Equation (1).

$$RMSE = \sqrt{mean\left(\left(y_{true} - y_{pred}\right)^2\right)} \quad (1)$$

3.4.2. Coefficient of Determination (R2)

Known as R^2, the coefficient of determination measures the goodness-of-fit for a regression model. R^2 values fall between 0 and 1, quantifying the amount of variability in the dependent variable explained by the independent variables.

It compares the model’s replicative ability against a baseline model that predicts the mean of the dependent variable. While R^2 is useful for assessingmodel fit, it should be used in conjunction with other metrics for a comprehensive Equation (2).

$$R^2 = 1 - \frac{SSres}{SStot} \quad (2)$$

3.4.3. Mean Squared Error (MSE)

MSE serves as another performance metric that calculates the average of squared differences between predicted and actual outcomes. A lower MSE value implies a better fit, and it lends greaterweight to larger errors, thus being a sensitive evaluation measure Equation (3).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (3)$$

3.4.4. Mean Absolute Error (MAE)

MAE, like MSE, calculates the average absolute discrepancies between predicted and actual values. It is often favored when the dataset contains outliers, as it is less sensitive to extreme values compared to MSE Equation (4).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (4)$$

3.4.5. Explained Variance Score (EVS)

EVS is another performance measure used to quantify how well the independent variables explain the variance in the dependent variable. It ranges from 0 to 1, with higher values indicating a better fit Equation (5).

$$EVS = 1 - \frac{Var(y_{true} - y_{pred})}{Var(y_{true})} \quad (5)$$

3.4.6. Mean Absolute Percentage Error (MAPE)

MAPE measures the average percentage error between predicted and actual values. Although frequently used in forecasting, its effectiveness is limited when actual values are close to zero or when outliers are present Equation (6).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\backslash\% \quad (6)$$

4. Experimental Setups

In our study, Google Colab Pro served as the primary computational platform, chosen for its powerful hardware and smooth integration capabilities with various data services. The availability of high-performance GPUs in Colab Pro was instrumental, especially when training resource-demanding models like LSTM, GRU, and WaveNet. We used Python as our main programming language, leveraging its vast array of dedicated libraries and frameworks for machine learning and data analysis. Tools like Pandas facilitated data handling, while Matplotlib and Seaborn assisted with visual representation. For the creation and assessment of our models, we utilized the capabilities of scikit-learn and TensorFlow. This environment, rich in features and flexibility, was pivotal in streamlining our experiments, allowing us to concentrate on in depth data examination and the assessment of model efficiency.

5. Results and Discussion

In this segment, we detail the results garnered from the predictive models formulated for assessing CS in construction endeavors. The primary objective was to cultivate models capable of dependably forecasting CS, a vital factor in guaranteeing the enduring stability and longevity of structures.

5.1. Results of Linear Regression

The evaluation of the linear regression model yielded insightful metrics that elucidate its capability in predicting outcomes. Notably, the model exhibited an RMSE value of approximately 9.7784. In the context of predicting CS for construction projects situated in British Columbia, this RMSE score reflects a commendable accuracy. Interpreted, this suggests that the model deviates, on average, by about 9.7784 units when predicting the target variable, an indication of a tight alignment with observed outcomes as shown in Table 1.

Table 1. Linear regression results.

Evaluation metric	RMSE	R^2	MSE	MAE	EV	MAPE
Linear regression	9.778	0.637	95.617	7.865	0.637	0.3316

Further insights into the model's adeptness can be drawn from the R2 value, registered at approximately 0.6370. Such a metric indicates that the model's independent variables account for roughly 63.7% of the variations in the CS, a significant proportion in the realm of predictive modeling. The MSE for the model stood at around 95.6172, while its MAE was gauged at about 7.8646. These values, in tandem, suggest that the model is proficient in discerning the underlying data patterns and maintains consistency in its predictions.

Further, the Explained Variance (EV) score, resonating closely with the R2 value, was determined to be approximately 0.6370. This reinforces the model's effectiveness in elucidating the discrepancies in the target variable. Concluding the performance metrics, the Mean Absolute Percentage Error (MAPE) was assessed to be around 0.3316 or 33.16%.

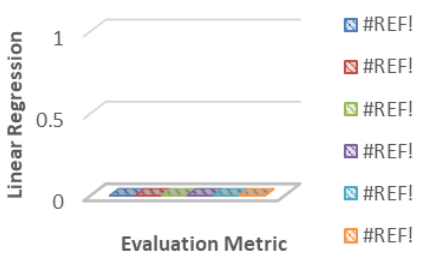

Figure 7. Linear regression for each model.

Such a figure insinuates that the model's predictions, on average, deviate from actual outcomes by a percentage that falls within conventional scientific acceptability as shown in Figure 7.

5.2. Results of Gated Recurrent Unit (GRU)

The GRU model's evaluation underscores its adeptness in forecasting CS for construction endeavors in British Columbia. A salient feature of its performance is the R2, registering at an enviable 0.8361. This metric implies that the model's predictors account for approximately 83.61% of the fluctuations in the CS. Such an elevated R2 illustrates a pronounced alignment with the observed data, demonstrating that the model aptly mirrors the intrinsic data dynamics as shown in Table 2.

Table 2. GRU model results.

Evaluation metric	RMSE	R2	MSE	MAE	EV	MAPE
GRU	9.778	0.637	95.617	7.865	0.637	0.332

Nevertheless, a comprehensive assessment necessitates considering the RMSE, which stands at roughly 22.2711 units. While seemingly elevated in light of the elevated R2, it becomes imperative to interpret this figure relative to the magnitude and scope of the dependent variable. The model's MSE is cataloged at about 43.175, a figure that leans towards the lower spectrum, bolstering confidence in the model's alignment with the data. Additionally, the model's MAE is benchmarked at about 4.934. This suggests modest average absolute deviations, a feature that holds weight in real-world applications.

Moreover, the EV metric, aligning closely with the R2, is determined to be 0.8361. This concordance underlines the model's efficacy in delineating the variances in the dependent variable. Rounding off the metrics, the MAPE is assessed to be a mere 0.1758 or 17.58%, underscoring a minimal percentage disparity between the model's forecasts and the actual values. In summation, the GRU model's predictive prowess is evident, rendering it a formidable instrument for prognosticating.

CS as displayed in Figure 8.

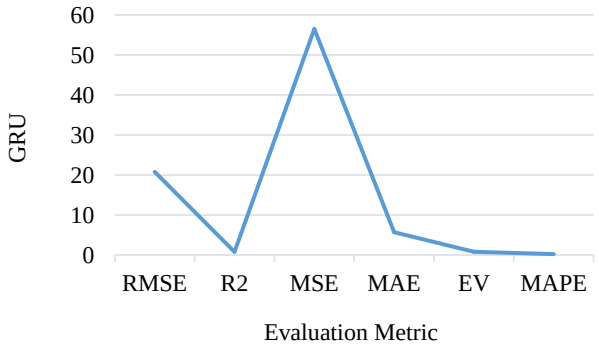

Figure 8. GRU model results.

5.3. Results of Long Short-Term Memory (LSTM)

The LSTM model, a popular recurrent neural network architecture, exhibited a persuasive performance spectrum across its evaluation metrics. Registering a RMSE of close to 20.79, it affirms the LSTM model's proficiency in predicting continuous values with commendable accuracy. It's imperative, though, to recognize that this RMSE value, marginally elevated relative to certain other models, suggests some fluctuation in prediction errors.

A pivotal metric, the R2, is tabulated at 0.7854. This value articulates that the LSTM model elucidates approximately 78.54% of the fluctuations inherent in the dependent variable, serving as a testament to the model's aptitude. The MSE is approximated at 56.53. Given its consonance with the RMSE, it accentuates the consistent reliability of the LSTM model.

Further, the model's MAE is charted at around 5.7014, implying an average deviation of nearly 5.70 units in its predictions. Notably, the LSTM's EV is pegged at 0.8025, signifying that it captures a substantial 80.25% of the dataset's inherent variance. To culminate the evaluation, the MAPE) is gauged at about 21.99% (or 0.2199). This suggests that, in terms of percentage disparities between actual and forecasted outcomes, the LSTM model manifests a relatively balanced error profile as shown in Table 3.

Table 3. LSTM results.

Evaluation metric	RMSE	R2	MSE	MAE	EV	MAPE
GRU	20.791	0.785	56.528	5.701	0.803	0.219

5.4. Results of WaveNet

The WaveNet model, a sophisticated deep learning architecture, demonstrated a formidable prowess in its predictive performance across multiple metrics, discerning complex nuances within the dataset. The model registered an RMSE close to 23.22. While this showcases the model's competence in mirroring true outcomes, it's slightly elevated compared to certain competing models.

The R2 value is noteworthy at 0.8846. This suggests that the WaveNet model accounts for an impressive 88.46% of the fluctuations within the dependent variable, underscoring its robust fit to the data. The derived MSE, approximately 30.38, is on the lower end of the spectrum, echoing the insights from the RMSE regarding the model's adeptness.

Table 4. WaveNet results.

Evaluation metric	RMSE	R2	MSE	MAE	EV	MAPE
WaveNet	23.224	0.885	30.383	3.465	0.887	0.122

The model's MAE, marked at roughly 3.47 units, indicates an average divergence of this magnitude from the ground truth, which speaks volumes about its accuracy. Further insights are gleaned from the EV Score which stands at a remarkable 0.8873. This suggests that the WaveNet model captures almost 88.73% of the intrinsic variance of the dataset, harmonizing with the findings from the R2 metric. Concluding the evaluation, the MAPE is measured at a mere 12.16% (or 0.1216), highlighting that the average percentage deviation between the model's forecasts and

the true values is commendably narrow as shown in Table 4.

6. Discussion

The comparative evaluation of the four diverse models-linear regression, LSTM, GRU, and WaveNet-in predicting CS elucidates varying degrees of precision and adaptability. Linear regression, serving as the foundational model, generated an RMSE close to 9.78 and an R2 of 0.637. This underscores its decent alignment with the data but indicates potential challenges in deciphering intricate patterns. Conversely, the GRU exhibited commendable outcomes, reflecting an R2 of 0.836. However, its elevated RMSE of 22.27 raises questions about its sensitivity to anomalous data points or outliers.

The LSTM model, hailing from the recurrent neural network family, registered an RMSE near 20.79 with an R2 reading of 0.785. While its results are praiseworthy, the GRU marginally overshadowed it in this context. The WaveNet model stole the limelight with its stellar R2 of 0.885 and a notably minimal MAPE of 0.122, indicating its top-tier alignment and adaptability to unfamiliar data instances. Intriguingly, the EV metrics for all models paralleled their respective R2 figures, reinforcing the reliability of the evaluation standards. Yet, WaveNet's slightly augmented RMSE at 23.22 warrants a deeper probe into the types of errors it might be more prone to.

7. Conclusions and Future Work

In wrapping up, our study introduces an innovative paradigm shift in forecasting concrete performance by skillfully amalgamating time-tested engineering techniques with cutting-edge machine learning methodologies. Our meticulous assessments revealed that sophisticated models, notably WaveNet and LSTM, conspicuously surpassed the conventional linear regression. To illustrate, WaveNet rendered a laudable R2 of 0.884 and an RMSE of 23.22, while LSTM presented an R2 of 0.785 accompanied by an RMSE of 20.79. Further, our fiscal examination accentuates the palpable advantages of embracing these avant-garde prediction techniques, emphasizing their superior technical prowess complemented by their economic viability.

Such revelations spotlight the transformative capacity of machine learning in reshaping the edifice of the construction sector, proffering solutions that are not only precise and enduring but also financially sustainable. Our integrative methodology stands as a model, exemplifying the harmonious convergence of civil engineering, computational analytics, and economic principles to confront intricate, tangible dilemmas. While our endeavor marks a significant stride, the expansive deployment and persistent enhancement of these algorithms possess the potential to radically influence the construction domain's trajectory, ushering an era dominated by sustainable, economical, and analytically grounded practices which will be as our future work. Also, as a future work we will use the sophisticated models like WaveNet and LSTM in different applications.

References

[1] Ahmad A., Ahmad W., Aslam F., and Joyklad P., "Compressive Strength Prediction of Fly Ash-Based Geopolymer Concrete Via Advanced Machine Learning Techniques," *Case Studies in Construction Materials*, vol. 16, pp. 00840, 2022. https://doi.org/10.1016/j.cscm.2021.e00840

[2] Ahmad A., Ahmad W., Chaiyasarn K., Ostrowski K.., and Aslam F., "Prediction of Geopolymer Concrete Compressive Strength Using Novel Machine Learning Algorithms," *Polymers*, vol. 13, no. 19, pp. 3389, 2021. https://doi.org/10.3390/polym13193389

[3] Ahmad A., Chaiyasarn K., Farooq F., Ahmad W., and Suparp S., "Compressive Strength Prediction Via Gene Expression Programming (GEP) and Artificial Neural Network (ANN) for Concrete Containing RCA," *Buildings*, vol. 11, no. 8, pp. 324, 2021. https://doi.org/10.3390/buildings11080324

[4] Ahmad M., Hu J., Ahmad F., Tang X., and Amjad M., "Supervised Learning Methods for Modeling Concrete Compressive Strength Prediction at High Temperature," *Materials*, vol. 14, no. 8, pp. 1983, 2021. https://doi.org/10.3390/ma14081983

[5] Aljadani E., Assiri F., and Alshutayri A., "Detecting Spam Reviews in Arabic by Deep Learning," *The International Arab Journal of Information Technology*, vol. 21, no. 3, pp. 495-505, 2024. DOI:10.34028/iajit/21/3/12

[6] Amin M., Iqbal M., Khan K., Qadir M., and Shalabi F., "Ensemble Tree-Based Approach Towards Flexural Strength Prediction of FRP Reinforced Concrete Beams," *Polymers*, vol. 14, no. 7, pp. 1303, 2022. https://doi.org/10.3390/polym14071303

[7] Chen S., Zhang S., Han W., and Wu G., "Ensemble Learning Based Approach for FRP-Concrete Bond Strength Prediction," *Construction and Building Materials*, vol. 302, pp. 124230, 2021. https://doi.org/10.1016/j.conbuildmat.2021.124230

[8] Concrete Compressive Strength (kaggle.com), https://www.kaggle.com/datasets/elikplim/concrete-compressive-strength-data-set, Last Visited, 2024.

[9] Dao D., Adeli H., Ly H., Le L., Le V., Le T., and Pham B., "A Sensitivity and Robustness Analysis of GPR and ANN for High-Performance Concrete Compressive Strength Prediction Using a Monte

Carlo Simulation," *Sustainability*, vol. 12, no. 3, pp. 830, 2020. https://doi.org/10.3390/su12030830

[10] Dargan S., Kumar M., Ayyagari M., and Kumar G., "A Survey of Deep Learning and its Applications: A New Paradigm to Machine Learning," *Archives of Computational Methods in Engineering*, vol. 27, pp. 1071-1092, 2020. https://doi.org/10.1007/s11831-019-09344-w

[11] DeRousseau M., Laftchiev E., Kasprzyk J., Rajagopalan B., and Srubar W., "A Comparison of Machine Learning Methods for Predicting the Compressive Strength of Field- Placed Concrete," *Construction and Building Materials*, vol. 228, pp. 116661, 2019. https://doi.org/10.1016/j.conbuildmat.2019.08.042

[12] Feng D., Liu Z., Wang X., Chen Y., and Chang J., "Machine Learning-Based Compressive Strength Prediction for Concrete: An Adaptive Boosting Approach," *Construction and Building Materials*, vol. 230, pp. 117000, 2020. https://doi.org/10.1016/j.conbuildmat.2019.117000

[13] Gupta S. and Sharma N., "Machine Learning Driven Threat Identification to Enhance FANET Security Using Genetic Algorithm," *The International Arab Journal of Information Technology*, vol. 21, no. 4, pp. 711-722, 2024. DOI:10.34028/iajit/21/4/12

[14] Haque M., Chen B., Kashem A., Qureshi T., and Ahmed A., "Hybrid Intelligence Models for Compressive Strength Prediction of MPC Composites and Parametric Analysis with SHAP Algorithm," *Materials Today Communications*, vol. 35, pp. 105547, 2023. https://doi.org/10.1016/j.mtcomm.2023.105547

[15] Kamath M., Kumar S., and Tantri A., "Machine-Learning-Algorithm to Predict the High-Performance Concrete Compressive Strength Using Multiple Data," *Journal of Engineering, Design and Technology*, vol. 22, no. 2, pp. 532-560, 2022. DOI:10.1108/JEDT-11-2021-0637

[16] Latif S., "Concrete Compressive Strength Prediction Modeling Utilizing Deep Learning Long Short-Term Memory Algorithm for a Sustainable Environment," *Environmental Science and Pollution Research,* vol. 28, no. 23, pp. 30294-30302, 2021. https://doi.org/10.1007/s11356-021-12877-y

[17] Mechelli A. and Vieira S., *Machine Learning Methods and Applications to Brain Disorder*, Elsevier, 2020. https://doi.org/10.1016/B978-0-12-815739-8.00004-3

[18] Oey T., Jones S., Bullard J., and Sant G., "Machine Learning Can Predict Setting Behavior and Strength Evolution of Hydrating Cement Systems," *Journal of the American Ceramic Society*, vol. 103, no. 1, pp. 480-490, 2020. https://doi.org/10.1111/jace.16706

[19] Qiu C., Gong S., and Gao W., "Three Artificial Intelligence-Based Solutions Predicting Concrete Slump," *UPB Scientific Bulletin*, vol. 81, no. 4, pp. 3-14, 2019. https://www.scientificbulletin.upb.ro/rev_docs_archiva/full0fc_432763.pdf

[20] Rahman J., Ahmed K., Khan N., Islam K., and Mangalathu S., "Data-Driven Shear Strength Prediction of Steel Fiber Reinforced Concrete Beams Using Machine Learning Approach," *Engineering Structures*, vol. 233, pp. 111743, 2021. https://doi.org/10.1016/j.engstruct.2020.111743

[21] Sarker I., "Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions," *SN Computer Science*, vol. 2, no. 420, pp. 1-20, 2021. https://doi.org/10.1007/s42979-021-00815-1

[22] Sarla P., Priya S., Ravindran G., Shyamsunder M., Sirikonda S., Sultana F., and Reddy C., "Forecasting the Analysis of Concrete Compressive Strength, Mass and NDT Results Using ARIMA Model," *in Proceedings of the International Conference on Research in Sciences, Engineering and Technology*, Warangal, 2022. https://doi.org/10.1063/5.0081945

[23] Song H., Ahmad A., Farooq F., Ostrowski K., and Maślak M., "Predicting the Compressive Strength of Concrete with Fly Ash Admixture Using Machine Learning Algorithms," *Construction and Building Materials*, vol. 308, pp. 125021, 2021. https://doi.org/10.1016/j.conbuildmat.2021.125021

[24] Thuillard M., *Advances in Computational Intelligence and Learning*: *Methods and Applications*, Springer, 2002. https://doi.org/10.1007/978-94-010-0324-7_3

[25] Tyagi A. and Abraham A., *Recurrent Neural Networks: Concepts and Applications*, CRC Press Tylor Francis Group, 2022. https://doi.org/10.1201/9781003307822

[26] Wan Z., Xu Y., and Šavija B., "On the Use of Machine Learning Models for Prediction of Compressive Strength of Concrete: Influence of Dimensionality Reduction on the Model Performance," *Materials*, vol. 14, no. 4, pp. 713, 2021. https://doi.org/10.3390/ma14040713

[27] Wang X., Liu Y., and Xin H., "Bond Strength Prediction of Concrete-Encased Steel Structures Using Hybrid Machine Learning Method," *Structures*, vol. 32, pp. 2279-2292, 2021. https://doi.org/10.1016/j.istruc.2021.04.018

[28] Zeng Z., Zhu Z., Yao W., Wang Z., and Wang C., "Accurate Prediction of Concrete Compressive Strength Based on Explainable Features Using Deep Learning," *Construction and Building Materials*, vol. 329, pp. 127082, 2022. https://doi.org/10.1016/j.conbuildmat.2022.127082

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