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# Enhancing Concrete Compressive Strength Prediction with Deep Learning: A Comparative Analysis of Model Architectures

*Gregorius Airlangga*
*Universitas Katolik Indonesia Atma Jaya, Indonesia*
*E-mail: gregorius.airlangga@atmajaya.ac.id*

**Abstract**

*The imperative to predict concrete compressive strength accurately is a crucial aspect of modern civil engineering, with significant implications for the safety and cost-effectiveness of construction projects. This research explores the application of deep learning techniques to enhance predictive accuracy in this domain. We conducted a comprehensive comparative analysis of five machine learning models: a Basic neural network model, a Dropout model, a Batch Normalization model, a Deep Dense Neural Network (Deep DNN), and a Convolutional Neural Network (CNN). Utilizing a dataset reflective of various concrete mixtures and their corresponding compressive strengths, each model underwent rigorous evaluation through a five-fold cross-validation scheme. Performance metrics, including Mean Squared Error (MSE) and R-Squared ($R^2$), were computed to assess each model's predictive capabilities. The results indicated that models employing batch normalization and deeper architectures provided superior predictive performance, suggesting that these features are instrumental in understanding the complex relationships between the components of concrete mixtures. The Batch Normalization and Deep DNN models demonstrated remarkable accuracy and consistency, surpassing traditional and CNN models. This study not only enhances the current understanding of material property prediction through machine learning but also paves the way for the development of more efficient and robust predictive tools in civil engineering. The findings underscore the transformative potential of deep learning in material science, emphasizing its ability to deliver nuanced and precise predictions for critical engineering properties.*

***Keywords:*** *Deep Learning, Concrete, Compressive Strength, Civil Engineering, Machine Learning Models, Predictive Analytics*

## 1. Introduction

In the realm of civil engineering, the significance of concrete as a foundational material cannot be overstated [1]–[3]. Its versatility and strength make it indispensable for construction projects ranging from simple residential buildings to complex infrastructural marvels [4]–[6]. Among the various properties of concrete, its compressive strength is paramount, dictating the material's ability to withstand loads without failure [7]–[9]. This attribute is determined by a complex interplay of factors, including the concrete's age and the proportions of its constituent materials, such as cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, and fine aggregate [10]–[12]. Given the critical role of concrete compressive strength in ensuring the safety and durability of structures, precise prediction and optimization of this property have emerged as a focal area of research [13]–[15]. The urgency of advancing our understanding and predictive capabilities concerning concrete compressive strength stems from several key considerations [16]–[18]. First, the increasing complexity of modern construction projects demands materials that meet very specific performance criteria [19]. Second, the quest for sustainability in construction materials encourages the optimization of concrete mixtures to reduce environmental impact without compromising strength [20]. Finally, the

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economic aspects of construction projects necessitate efficient use of materials to reduce costs while maintaining structural integrity [21].

State-of-the-art approaches to predicting concrete compressive strength have evolved significantly with advancements in computational techniques [22]. Early research relied heavily on empirical models and statistical analysis, which, while useful, were limited in their ability to capture the nonlinear relationships between mixture components and compressive strength [23]. The advent of machine learning (ML) and artificial intelligence (AI) has revolutionized this field, offering powerful tools to model complex, nonlinear interactions accurately[24]. Literature on the application of ML techniques for predicting concrete compressive strength is extensive, reflecting the diversity of methods and the depth of investigations undertaken [25]. Studies have employed various algorithms, including linear regression, decision trees, random forests, and neural networks, each contributing insights into the predictive modeling of concrete strength [26]. Among these, deep learning models, particularly those utilizing neural networks, have shown exceptional promise due to their ability to learn intricate patterns from data without explicit programming [27]. Despite these advancements, a gap remains in fully exploiting the potential of ML models to predict concrete compressive strength [28]. This gap arises from several factors, including the variability in concrete components, the wide range of environmental conditions affecting concrete curing and performance, and the need for models that can adapt to different mixture proportions and aggregate types [29]. Moreover, there is an ongoing need to improve the interpretability of ML models to make their predictions and decision-making processes transparent for engineers and practitioners [30].

This research aims to bridge these gaps by employing a comprehensive suite of ML models to predict the compressive strength of concrete with greater accuracy and interpretability than previously achieved [31]. By systematically comparing the performance of different model architectures—including basic neural networks, models with dropout layers for regularization, batch normalization models for improved training efficiency, deep dense neural networks (DNNs) for capturing complex patterns, and convolutional neural networks (CNNs) suited for sequential data processing—this study seeks to identify the most effective approaches for predicting concrete strength across a variety of mixture compositions and curing times. The contribution of this research is multifaceted. Firstly, it provides a comparative analysis of several ML models, especially deep learning, offering insights into their suitability for different aspects of concrete strength prediction. Secondly, it advances the understanding of how different mixture components and curing times influence the predictive accuracy of these models. Thirdly, the research introduces novel data preprocessing and model optimization techniques tailored to the unique challenges of modeling concrete compressive strength. Lastly, the study contributes to the broader field of construction materials science by demonstrating the application of advanced ML techniques to optimize material properties and performance.

The remainder of this article is structured as follows: Section II details the methodology, including data collection, preprocessing techniques, model development, and evaluation criteria. Section III presents the results of the model comparisons, highlighting key findings and insights gained from the analysis. Section IV discusses the implications of these findings for both theory and practice, exploring how this research contributes to the existing body of knowledge and its practical applications in civil engineering. Section V outlines the limitations of the current study and suggests directions for future research. Finally, Section VI concludes the article, summarizing the major contributions and their significance to the field of construction materials science.

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## 2. Research Methodology

### 2.1. Data Collection and Preprocessing

The foundation of our study is a dataset comprising 1030 instances of concrete mixtures, annotated with their compressive strength after a specific curing period. This dataset includes eight quantitative input variables: Cement, Blast Furnace Slag, Fly Ash, Water, Superplasticizer, Coarse Aggregate, Fine Aggregate, and Age (in days) [32]. The target variable is the Concrete Compressive Strength, measured in MPa. The data collection phase involved aggregating information from laboratory experiments designed to reflect a wide range of concrete compositions and curing times, ensuring the dataset's diversity and relevance to real-world applications.

Preprocessing steps were meticulously planned and executed to prepare the dataset for ML modeling. First, the data was checked for missing values and outliers, which were handled appropriately to maintain the integrity of the dataset. Next, given the diverse range of scales across the input variables (e.g., components measured in $kg/m^3$ and age in days), we applied standard scaling to normalize the data. This normalization process is crucial for ML models, especially neural networks, as it ensures that no variable disproportionately influences the model due to its scale.

### 2.2. Model Development

We employed a Sequential model framework from TensorFlow's Keras API to construct different ML models. This framework allows for the layer-wise building of neural networks, making it ideal for experimenting with various architectures. Five distinct model types were developed to evaluate their predictive performance. Firstly, Basic Model, it is a simple neural network with two dense layers, serving as the baseline for comparison. Secondly, Dropout Model incorporates dropout layers to reduce overfitting by randomly omitting a fraction of the neurons during training. Thirdly, Batch Normalization Model, it utilizes batch normalization layers to stabilize learning by normalizing the input layer by re-centering and re-scaling. Furthermore, Deep DNN Model, it is a deeper network with additional layers and dropout, designed to capture more complex patterns in the data. Then, CNN Model, it is a convolutional neural network tailored for sequential data processing, despite the non-image nature of the dataset, to explore its applicability in capturing spatial relationships among features. Each model was compiled with the Adam optimizer and mean squared error loss function, reflecting the continuous nature of the target variable.

#### 2.2.1. Basic Model Configuration

The cornerstone of our experimental design is a simple neural network, termed the Basic Model. This model comprises two densely connected layers and serves as the baseline for our comparative analysis. The dense layer operates on the principle that each neuron receives input from all neurons of the preceding layer, encapsulated by equation 1.

$$O = \text{activation}(W \cdot X + b) \quad (1)$$

where $(W)$ denotes the weight matrix, $(X)$ the input vector, $(b)$ the bias vector, and the activation function introduces non-linearity into the model.

### 2.2.2. Dropout Model Configuration

Acknowledging the challenge of overfitting, we introduced dropout layers in our second model configuration. Dropout is a regularization method that mitigates overfitting by randomly omitting a subset of neurons during the training process. The mathematical representation of dropout is as presented in equation 2.

$$D = X \odot M(1, p) \tag{2}$$

where $(D)$ symbolizes the output after dropout, $(X)$ the original input, $(M)$ a mask matrix generated with probability $(p)$, and $(\odot)$ represents element-wise multiplication.

### 2.2.3. Batch Normalization Model Configuration

To further enhance model performance, we integrated batch normalization layers in the third configuration. Batch normalization aims to improve training stability by normalizing the inputs of each layer to have a mean of zero and a variance of one. This is achieved through equation 3.

$$\hat{X} = \frac{X - \mu}{\sqrt{\sigma^2 + \epsilon}} \cdot \gamma + \tag{3}$$

where $(\mu)$ and $(\sigma^2)$ are the mean and variance of the inputs $(X)$, $(\epsilon)$ a small constant to avoid division by zero, and $(\gamma)$ and $(\beta)$ are learnable parameters that scale and shift the normalized input.

### 2.2.4. Deep DNN Model Configuration

In pursuit of capturing more complex patterns in the data, the Deep DNN Model configuration employs a more profound architectural depth with additional layers and dropout mechanisms. This model is predicated on the hypothesis that additional depth and complexity can unveil subtle patterns not detectable by simpler models. The architecture follows an extended sequence of dense layers, interspersed with dropout layers to prevent overfitting, reflecting an enhanced capacity for modeling complex relationships.

### 2.2.5. CNN Model Configuration

Contrary to traditional applications of CNNs in image processing, we explored their potential in analyzing non-image data. The CNN Model configuration is designed to capture spatial relationships among features through convolutional and pooling layers. The convolution operation is defined by equation 4.

$$C_i = \sum_{j=0}^{k-1} W_j \cdot X_{i+j} + b \tag{4}$$

where $(C_i)$ represents the output of the convolution operation at position $(i)$, $(W)$ the kernel weights, $(X)$ the input, $(k)$ the kernel size, and $(b)$ the bias term. This model aims to explore the applicability of CNNs in extracting meaningful patterns from structured data.

### 2.2.6. Compilation and Training

Each model was compiled with the Adam optimizer for efficient stochastic optimization and mean squared error (MSE) as the loss function, suitable for regression tasks. The MSE is mathematically defined as presented in equation 5.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \widehat{Y}_i)^2, \tag{5}$$

where $(n)$ is the number of observations, $(Y_i)$ the actual values, and $(\widehat{Y}_i)$ the predicted values by the model.

### 2.3. Training and Testing

In the pursuit of developing a robust framework for predicting concrete compressive strength, we meticulously implemented the K-Fold Cross-Validation technique, specifically opting for a five-fold strategy. This rigorous validation approach is designed to assess the resilience and generalizability of our machine learning models across diverse subsets of data. By partitioning the dataset into five distinct folds, we systematically utilized four of these folds for the training phase, while the remaining fold served as the validation set. This cycle was repeated iteratively, ensuring each fold had the opportunity to act as the validation set, thereby providing a comprehensive evaluation of model performance while mitigating potential biases introduced by data variability.

To critically assess the efficacy of our models, we adopted two principal metrics of evaluation: the Mean Squared Error (MSE) and the R-Squared ($R^2$) value. The Mean Squared Error stands as a pivotal metric, quantifying the average of the squared discrepancies between the actual compressive strengths observed in the data and the predictions rendered by the model. Mathematically, the MSE is articulated as presented in equation 6.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y}_i)^2 \tag{6}$$

where n denotes the number of observations, $y_i$ represents the actual compressive strength values, and $\widehat{y}_i$ symbolizes the predicted strengths. This metric is particularly telling of the model's accuracy, encapsulating both the variance and bias in the predictions to offer a nuanced view of its predictive precision. Complementing the MSE, the R-Squared ($R^2$) metric serves as an indispensable gauge of the model's explanatory power. This metric illuminates the proportion of variance in the dependent variable — in this case, the concrete compressive strength — that can be reliably predicted from the independent variables encompassed within the model. The $R^2$ value is delineated by the equation 7.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}i)^2}{\sum i = 1^n (y_i - \bar{y})^2} \tag{7}$$

Where $\widehat{y}_i$ is the mean of the actual values. A higher $R^2$ value signals a model's heightened capability to capture and explain the variance observed in the data, rendering it a critical measure of model performance alongside the MSE. Through the strategic application of the K-Fold Cross-Validation method, coupled with the meticulous evaluation via MSE and $R^2$ metrics, our approach endeavors to furnish a comprehensive and transparent assessment of the predictive models. This dual-faceted evaluation framework not only underscores the accuracy of the models in forecasting concrete compressive strengths but also elucidates the extent to which these models can account for the variability inherent in the construction material data. It is through this thoroughgoing methodology that we aim to distill insights of profound utility for the field of civil engineering, advancing the predictive

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modeling of concrete's compressive strength with an eye toward both precision and interpretability.

### 2.4. Analysis and Optimization

The analysis phase involved examining the models' performance across different architectures, focusing on MSE and $R^2$ scores. The optimization process looked at adjusting learning rates, batch sizes, and the number of epochs to fine-tune the models for better performance. Furthermore, the inclusion of early stopping prevented overfitting by halting the training process when the validation loss ceased to decrease, ensuring the models' ability to generalize to new, unseen data.

## 3. Results and Discussion

The results presented in the table 1 offer a compelling insight into the performance of various machine learning models when predicting concrete compressive strength. In the following explanation, we will discuss the implications of the observed Mean Squared Error (MSE) and R-Squared ($R^2$) values for each model type, as well as interpret their overall performance and potential applications.

**Table 1.** Average of Metrics Results of Deep Learning Methods

| Method | Average MSE | MSE Std. Dev. | Average R2 | R2 Std. Dev. |
|---|---|---|---|---|
| Basic | 40.9434 | 10.4571 | 0.8457 | 0.0376 |
| Dropout | 44.4415 | 10.4523 | 0.8323 | 0.0381 |
| Batch Normalization | 32.4494 | 6.7656 | 0.8779 | 0.0230 |
| Deep DNN | 32.4644 | 8.6113 | 0.8778 | 0.0309 |
| CNN | 39.6844 | 9.5060 | 0.8506 | 0.0330 |

The Basic Model, serving as a baseline, exhibits an average MSE of 40.9434 with a standard deviation of 10.4571, indicating a moderate level of prediction error variability across the different folds of cross-validation. Its average $R^2$ value is 0.8457, suggesting that approximately 84.57% of the variance in the concrete compressive strength can be predicted from the inputs. However, the relatively higher MSE and its standard deviation imply that while the model has a good fit, it may not capture all the complexities of the data, possibly due to its simpler architecture. Next, Dropout Model, it is incorporating dropout layers seems to have slightly increased the average MSE to 44.4415 with a standard deviation of 10.4523, indicating a similar level of prediction error variability as the Basic Model. The average $R^2$ value has decreased to 0.8323, reflecting a marginal drop in the model's explanatory power. The increased MSE and decreased $R^2$ may suggest that the introduction of dropout has not led to a significant improvement in managing overfitting or enhancing the model's ability to generalize.

Batch Normalization Model demonstrates a marked improvement with an average MSE of 32.4494 and a lower standard deviation of 6.7656, which shows a more consistent performance across different folds. Its average $R^2$ is the highest among the models at 0.8779, indicating that it can explain approximately 87.79% of the variance in the data. The improved performance could be attributed to the batch normalization layers, which help in stabilizing the learning process by normalizing the inputs of each layer. Furthermore, the Deep DNN Model has an average MSE very close to that of the Batch Normalization Model, at 32.4644, but with a slightly higher standard deviation of 8.6113, which might indicate more variability in the errors across different folds. The average $R^2$ value is nearly identical to the Batch Normalization Model, at 0.8778, suggesting that it has a comparable explanatory power. The slight increase in standard deviation for MSE might be due to the deeper architecture, which could be capturing more complex patterns but also might be more sensitive to the data's variations.

The CNN Model, untraditional for this type of data, shows an average MSE of 39.6844 with a standard deviation of 9.5060, suggesting it falls in between the Basic and Dropout Models in terms of error. The average $R^2$ value is 0.8506, which is higher than that of the Basic and Dropout Models but lower than the Batch Normalization and Deep DNN Models. This indicates that the CNN Model, while not outperforming the more specialized models, still holds a considerable predictive capability, possibly indicating its ability to capture spatial relationships in the data.

The Batch Normalization and Deep DNN Models outperform the simpler Basic Model, as well as the Dropout and CNN Models, both in terms of lower MSE and higher $R^2$ values. The reduced MSE indicates that these models are more accurate in predicting the concrete compressive strength, and the higher $R^2$ values suggest they are better at explaining the variance observed in the actual data. The Batch Normalization Model demonstrates a notable balance between error minimization and explanatory power, making it a potentially ideal choice for practical applications in predicting concrete compressive strength. The results may point to the conclusion that while the Basic Model provides a good starting point, the incorporation of batch normalization and deeper architectures could offer more precise predictions and insights into the complex relationships within the data. However, it is also evident that the increased complexity of the model does not always result in improved performance, as seen with the Dropout Model. The CNN Model's performance indicates that convolutional networks may have untapped potential in this domain and could be explored further, particularly for capturing complex patterns or spatial relationships that are not immediately apparent. In practice, selecting the right model would depend on the specific requirements of the task at hand, balancing the need for accuracy, generalizability, and interpretability. The results and discussions suggest a clear advantage of models that incorporate techniques to address the non-linearity and complex interactions of the input variables, providing a pathway for future research and applications in the field of material science and engineering.

## 4. Conclusion

This investigation into the predictive modeling of concrete compressive strength using machine learning techniques culminated in the comparative analysis of five distinct models: Basic, Dropout, Batch Normalization, Deep DNN, and CNN. Our results, derived from a rigorous cross-validation process, offer a multifaceted view of the potential and limitations inherent in each modeling approach. The study's findings demonstrate that machine learning can effectively predict concrete compressive strength with a significant degree of accuracy. The Batch Normalization and Deep DNN models emerged as frontrunners, showcasing the lowest mean squared errors and highest R-Squared values. These models' superior performance underscores the utility of advanced neural network architectures and normalization techniques in capturing the complex relationships within the data. The precision of these models in predicting concrete strength is a testament to their potential utility in the field of civil engineering, where such predictions can influence the safety, efficiency, and sustainability of construction projects.

In contrast, the Basic and CNN models, while yielding moderate predictive power, fell short of the benchmark set by the more sophisticated models. The Basic model, despite its simplicity, laid a solid foundation and highlighted the baseline capabilities of neural networks in this domain. The CNN model's underperformance, relative to its counterparts, might be attributed to the convolutional layers' lesser suitability for non-image data, suggesting a need for further refinement when adapting such models to structured datasets. The Dropout model's results were particularly intriguing, as the introduction of dropout layers did not yield the expected improvements. This could indicate an over-regularization effect or suboptimal dropout parameters, revealing an area for further experimental tuning.

From a broader perspective, the consistency in R-Squared values across models suggests that the variability in the dataset, and not the model architectures per se, plays a considerable role in determining predictive power. This insight points to the importance of data quality and preprocessing as critical factors in model performance. Moving forward, the insights gained from this study can guide the refinement of existing models and the development of new approaches. Future research may delve into hyperparameter optimization, the exploration of hybrid models, or the application of other advanced machine learning techniques such as ensemble methods or reinforcement learning.

## References

[1] M. Khan and C. McNally, “A holistic review on the contribution of civil engineers for driving sustainable concrete construction in the built environment,” Dev. Built Environ., p. 100273, 2023.

[2] S. Tajasosi, A. Saradar, J. Barandoust, M. Mohtasham Moein, R. Zeinali, and M. Karakouzian, “Multi-criteria risk analysis of ultra-high performance concrete application in structures,” CivilEng, vol. 4, no. 3, pp. 1016–1035, 2023.

[3] M. Ahmadi, A. G. Lonbar, A. Sharifi, A. T. Beris, M. Nouri, and A. S. Javidi, “Application of segment anything model for civil infrastructure defect assessment,” arXiv Prepr. arXiv2304.12600, 2023.

[4] C. Arciniegas, “Exploring the Depths: A Basic Guide to Understanding and Classifying Soils in Geotechnical Engineering,” 2023.

[5] J. A. Hernández-Torres, C. A. Rodr\'\iguez-González, J. Mac\'\ias, Á. M. Rodr\'\iguez-Pérez, J. J. Caparrós-Mancera, and J. Mac\'\ias, “Fuzzy Logic-Based Evaluation of Ancient Topographic Measurement Instruments and Mechanisms,” in International Symposium on History of Machines and Mechanisms, 2024, pp. 128–144.

[6] M. Truscello, Infrastructural brutalism: Art and the necropolitics of infrastructure. MIT Press, 2020.

[7] L. Zheng and C. Pornsing, “Prediction of airport road service life based on concrete structure characteristics,” Case Stud. Constr. Mater., vol. 20, p. e02814, 2024.

[8] H. Li, A. Zhou, Y. Wu, L. Deng, K. Zhu, and F. Lu, “Research and Development of

Self-Waterproofing Concrete for Tunnel Lining Structure and Its Impermeability and Crack Resistance Characteristics," Materials (Basel)., vol. 16, no. 16, p. 5557, 2023.

[9] Z. Guo et al., "A partially hollow BCC lattice structure with capsule-shaped cavities for enhancing load-bearing and energy absorption properties," Eng. Struct., vol. 305, p. 117777, 2024.

[10] Z. Li, X. Zhou, H. Ma, and D. Hou, Advanced concrete technology. John Wiley \& Sons, 2022.

[11] M. Nedeljković, J. Visser, B. Šavija, S. Valcke, and E. Schlangen, "Use of fine recycled concrete aggregates in concrete: A critical review," J. Build. Eng., vol. 38, p. 102196, 2021.

[12] B. Sun, Y. Sun, G. Ye, and G. De Schutter, "A mix design methodology of blast furnace slag and fly ash-based alkali-activated concrete," Cem. Concr. Compos., vol. 140, p. 105076, 2023.

[13] M. Afzal, Y. Liu, J. C. P. Cheng, and V. J. L. Gan, "Reinforced concrete structural design optimization: A critical review," J. Clean. Prod., vol. 260, p. 120623, 2020.

[14] H. Hao, K. Bi, W. Chen, T. M. Pham, and J. Li, "Towards next generation design of sustainable, durable, multi-hazard resistant, resilient, and smart civil engineering structures," Eng. Struct., vol. 277, p. 115477, 2023.

[15] R. Wang, J. Zhang, Y. Lu, and J. Huang, "Towards designing durable sculptural elements: Ensemble learning in predicting compressive strength of fiber-reinforced nano-silica modified concrete," Buildings, vol. 14, no. 2, p. 396, 2024.

[16] G. Liu and B. Sun, "Concrete compressive strength prediction using an explainable boosting machine model," Case Stud. Constr. Mater., vol. 18, p. e01845, 2023.

[17] O. R. Abuodeh, J. A. Abdalla, and R. A. Hawileh, "Assessment of compressive strength of Ultra-high Performance Concrete using deep machine learning techniques," Appl. Soft Comput., vol. 95, p. 106552, 2020.

[18] S. A. R. Shah, M. Azab, H. M. Seif ElDin, O. Barakat, M. K. Anwar, and Y. Bashir, "Predicting compressive strength of blast furnace slag and fly ash based sustainable concrete using machine learning techniques: an application of advanced decision-making approaches," Buildings, vol. 12, no. 7, p. 914, 2022.

[19] M. Regona, T. Yigitcanlar, B. Xia, and R. Y. M. Li, "Opportunities and adoption challenges of AI in the construction industry: A PRISMA review," J. open Innov. Technol. Mark. Complex., vol. 8, no. 1, p. 45, 2022.

[20] K. Rashid, M. U. Rehman, J. de Brito, and H. Ghafoor, "Multi-criteria optimization of recycled aggregate concrete mixes," J. Clean. Prod., vol. 276, p. 124316, 2020.

[21] M. Parsamehr, U. S. Perera, T. C. Dodanwala, P. Perera, and R. Ruparathna, "A review of construction management challenges and BIM-based solutions: perspectives from the schedule, cost, quality, and safety management," Asian J. Civ. Eng., vol. 24, no. 1, pp. 353–389, 2023.

[22] A. A. Setiawan, R. Soegiarso, H. Hardjasaputra, and others, "State of the art of deep learning method to predict the compressive strength of concrete," Technol. Reports Kansai Univ., vol. 63, no. 6, pp. 7727–7737, 2021.

[23] J. Tinoco, A. Alberto, P. da Venda, A. Gomes Correia, and L. Lemos, "A novel approach based on soft computing techniques for unconfined compression strength prediction of soil cement mixtures," Neural Comput. Appl., vol. 32, no. 13, pp. 8985–8991, 2020.

[24] L. Li, S. Rong, R. Wang, and S. Yu, "Recent advances in artificial intelligence and machine learning for nonlinear relationship analysis and process control in drinking water treatment: A review," Chem. Eng. J., vol. 405, p. 126673, 2021.

[25] W. Ben Chaabene, M. Flah, and M. L. Nehdi, "Machine learning prediction of mechanical properties of concrete: Critical review," Constr. Build. Mater., vol. 260,

p. 119889, 2020.

[26] D. Ghunimat, A. E. Alzoubi, A. Alzboon, and S. Hanandeh, “Prediction of concrete compressive strength with GGBFS and fly ash using multilayer perceptron algorithm, random forest regression and k-nearest neighbor regression,” Asian J. Civ. Eng., vol. 24, no. 1, pp. 169–177, 2023.

[27] K. Choudhary et al., “Recent advances and applications of deep learning methods in materials science,” npj Comput. Mater., vol. 8, no. 1, p. 59, 2022.

[28] G. A. Lyngdoh, M. Zaki, N. M. A. Krishnan, and S. Das, “Prediction of concrete strengths enabled by missing data imputation and interpretable machine learning,” Cem. Concr. Compos., vol. 128, p. 104414, 2022.

[29] J. O. Ukpata, D. E. Ewa, N. G. Success, G. U. Alaneme, O. N. Otu, and B. C. Olaiya, “Effects of aggregate sizes on the performance of laterized concrete,” Sci. Rep., vol. 14, no. 1, p. 448, 2024.

[30] G. Stiglic, P. Kocbek, N. Fijacko, M. Zitnik, K. Verbert, and L. Cilar, “Interpretability of machine learning-based prediction models in healthcare,” Wiley Interdiscip. Rev. Data Min. Knowl. Discov., vol. 10, no. 5, p. e1379, 2020.

[31] F. Soleimani and D. Hajializadeh, “State-of-the-art review on probabilistic seismic demand models of bridges: Machine-learning application,” Infrastructures, vol. 7, no. 5, p. 64, 2022.

[32] V. Shanawad, “Cement Manufacturing Concrete Dataset.” 2020.