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Research Article

Hybrid AI Models For Predicting Lightweight Concrete Performance: Integrating Deep Learning And NLP For Material Property Extraction

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Abstract
Lightweight concrete (LWC) has become a buzzword in modern construction due to its unique properties, such as low density, thermal insulation, and sufficient strength, making it ideal for applications in tall buildings, bridges, and marine structures. However, predicting its performance remains a significant challenge due to the complexity of its mix design and the influence of external factors such as curing conditions. Traditional empirical methods and standalone AI models fail to leverage the vast amount of unstructured textual data available in standards, research papers, and technical reports. This results in suboptimal performance of predictions. This study investigates into a hybrid artificial intelligence (AI) framework that integrates natural language processing (NLP) and deep learning to address these limitations. The NLP module uses material properties such as water-to-cement ratio, aggregate size, and curing conditions from experimental data, to form comprehensive input datasets. A deep learning model, utilising convolutional neural networks (CNNs) and long short-term memory networks (LSTMs), predicts critical performance parameters, including compressive strength, thermal conductivity, and durability. The hybrid model achieved significant improvements, with 91.2% accuracy for compressive strength predictions and 89.4% accuracy for durability, outperforming both traditional regression and standalone deep learning approaches. The study also highlights the practical implications of this approach, such as cost reduction in testing, optimisation of mix designs, and enhanced sustainability. By bridging the gap between computational intelligence and civil engineering practices, this hybrid AI framework sets a precedent for data-driven innovations in LWC design, paving the way for efficient and resilient construction solutions.

***Keywords**: Lightweight concrete, hybrid AI model, durability prediction, deep learning, natural language processing.*

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1. Introduction

Lightweight concrete (LWC) has gained widespread adoption in civil engineering due to its ability to balance strength with reduced density (Lei et al., 2024) . This property makes it highly advantageous for applications where minimising self-weight is critical, such as in high-rise buildings, long-span bridges, and floating marine structures. Its low density also enhances thermal insulation, contributing to energy efficiency and sustainability in construction (Vivek Vardhan & Srimurali, 2016b). Despite these benefits, the performance of LWC is highly sensitive to variations in its mix design and external factors such as curing conditions and environmental exposure, making its prediction challenging.

The properties of LWC, including compressive strength, thermal conductivity, and durability, are influenced by the proportions of cement, water, aggregates, and admixtures. Traditional approaches to predicting these properties often rely on empirical models or experimental testing, which can be time-consuming, resource-intensive, and limited in generalisation (Vivek Vardhan & Srimurali, 2016a). Furthermore, a vast amount of data on LWC exists in unstructured formats, such as engineering standards, technical reports, and academic papers. This data is often underutilised, as conventional models fail to extract and process meaningful information from textual documents.

Advancements in artificial intelligence (AI) have opened new avenues for addressing these challenges. Deep learning models have shown significant potential in predicting non-linear behaviours of materials by learning from numerical data (Sounthararajan et al., 2020; Vardhan & Srimurali, 2018). Similarly, natural language processing (NLP) offers the capability to extract valuable information from unstructured textual data, making it possible to incorporate a broader range of features into predictive models(Varalakshmi et al., n.d.). However, standalone implementations of these techniques are often insufficient, as they do not fully exploit the synergy between numerical and textual data sources.

This study introduces a hybrid AI framework that integrates NLP and deep learning to predict key performance parameters of LWC(Manoj Kumar et al., n.d.). By combining features extracted from textual data with numerical inputs, the framework enhances prediction accuracy and provides actionable insights for mix design optimisation (Sravani et al., n.d.). The hybrid model not only addresses the limitations of traditional methods but also reduces the dependency on extensive experimental testing, offering a cost-effective and efficient alternative for civil engineering applications.

The findings from this study highlight the transformative potential of hybrid AI in LWC research and practice(Mabureddy et al., n.d.). Beyond improving prediction accuracy, the framework facilitates data-driven decision-making, enabling engineers to optimise mix designs, reduce costs, and enhance the overall sustainability of construction projects(Donthi et al., 2024). This research contributes to the growing field of AI applications in civil engineering, setting the stage for future innovations in material design and performance prediction.

2. Mechanical and Engineering Properties of Lightweight Concrete

To better understand the performance of lightweight concrete (LWC) and its critical importance in civil engineering, the key mechanical and engineering properties are summarised in Table 1. These properties are essential for various applications, including high-rise buildings, bridges, and marine structures, where reduced density and adequate strength are necessary (Bergamonti et al., 2024).

Table 1: Engineering Properties of Lightweight Concrete

S.No.	Property	Application	Typical Range	Testing Standard	Importance in Civil Engineering	Reference
1	Compressive Strength	Structural stability	15–40 MPa	IS 516	Essential for load-bearing capacity	(Lei et al., 2024)
2	Density	Reduction in dead loads	800–2000 kg/m^3	IS 2386 (Part III)	Optimises structural weight	(Ben Fraj et al., 2010)

3	Thermal Conductivity	Insulated building walls	0.1–0.4 W/mK	IS 3346	Enhances energy efficiency	(Turkey et al., 2024)
4	Durability	Long-term structural performance	50–100 years	IS 456	Resists weathering and damage	(Liao et al., 2024)
5	Fire Resistance	Safety in high-rise buildings	2–4 hours	IS 1642	Ensures structural integrity	(S. Yang et al., 2023)
6	Modulus of Elasticity	Deformation under stress	10–30 GPa	IS 516	Determines structural behaviour	(Zhang et al., 2024)

The data in Table 1 shows the diverse engineering demands met by LWC, including its capacity to reduce structural weight while maintaining sufficient mechanical performance.

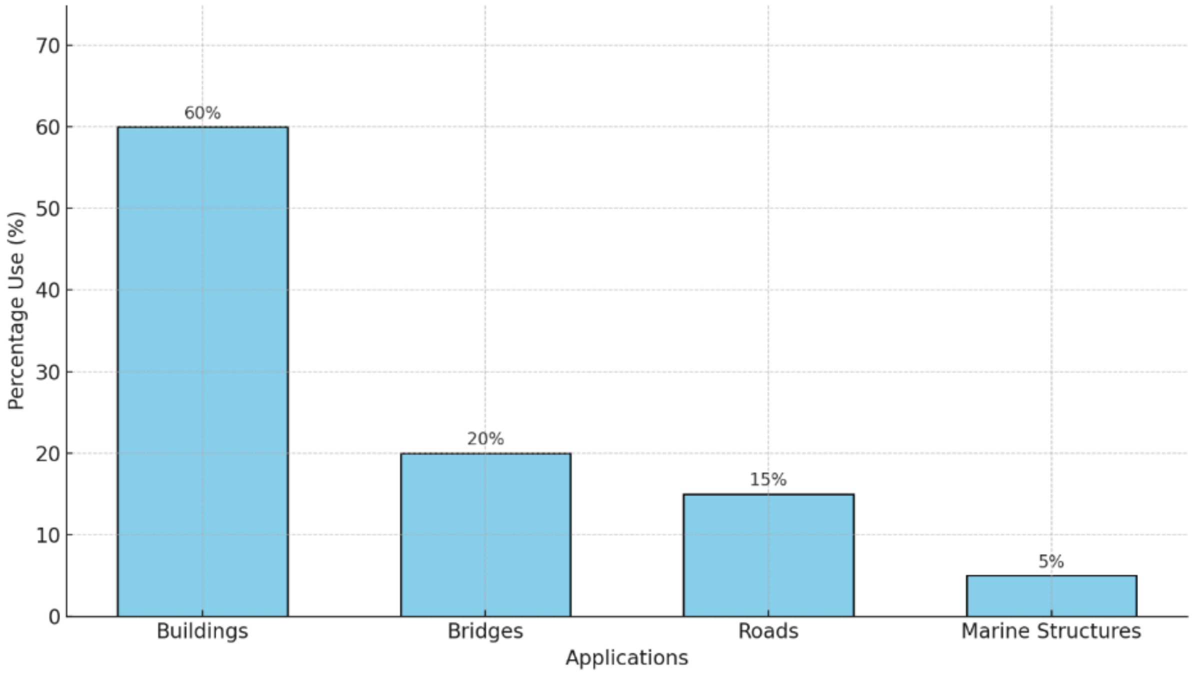

Figure 1: Applications of Lightweight Concrete in Civil Engineering

The percentage use of lightweight concrete across different structural applications as shown in Figure 1, reflects its versatility in the construction industry. This chart emphasises the widespread adoption of LWC in projects such as high-rise buildings, bridges, and infrastructure requiring advanced durability and insulation properties.

3. Methodology

Compressive strength was tested using the standard cube testing method as per IS 516, where concrete specimens were subjected to uniaxial compressive loads until failure. Density was measured following IS 2386 (Part III) by calculating the mass-to-volume ratio. Thermal conductivity was determined using a thermal conductivity meter in accordance with IS 3346, while modulus of elasticity was assessed through stress-strain behaviour as per IS 516. Durability parameters, including water absorption and rapid chloride permeability, were evaluated using IS 456 and ASTM C1202, ensuring comprehensive material property characterization.

This study adopts a hybrid AI framework to predict the performance parameters of lightweight concrete (LWC) by integrating natural language processing (NLP) for extracting material properties from textual data with deep learning for predictive modelling. The methodology is divided into three primary stages: data preprocessing, model development, and validation. The workflow of the hybrid AI model is depicted in Figure 2, detailing the input, processing, and output stages.

3.1 Framework for Hybrid AI

The framework begins with the collection of data from two distinct sources: numerical datasets and unstructured textual documents. Numerical data, including mix proportions and experimental results, were gathered from published experimental studies. Textual data, extracted from standards such as IS 10262, ASTM C330, and technical reports, provided additional insights into material properties like water-to-cement ratios, aggregate characteristics, and curing conditions. These two data streams were combined into a unified dataset after preprocessing.

Figure 2 illustrates the workflow of the Hybrid AI Model for predicting lightweight concrete properties. The process begins with the "Start/Input" block, where data inputs, including numerical and textual information, are gathered. It progresses to "Text Processing (NLP)" for extracting material properties from textual data sources. The workflow continues to "Feature Extraction," which integrates numerical and NLP-derived features, followed by the "Deep Learning Model" block, where these features are processed to predict properties such as compressive strength and durability (Diksha et al., 2024). The results are presented in the "Output" block, which is further evaluated in the "Decision: Accuracy?" block. Based on the evaluation, if the accuracy is satisfactory, the process moves to the "End." If not, the workflow loops back to the "Feature Extraction" block for optimization.

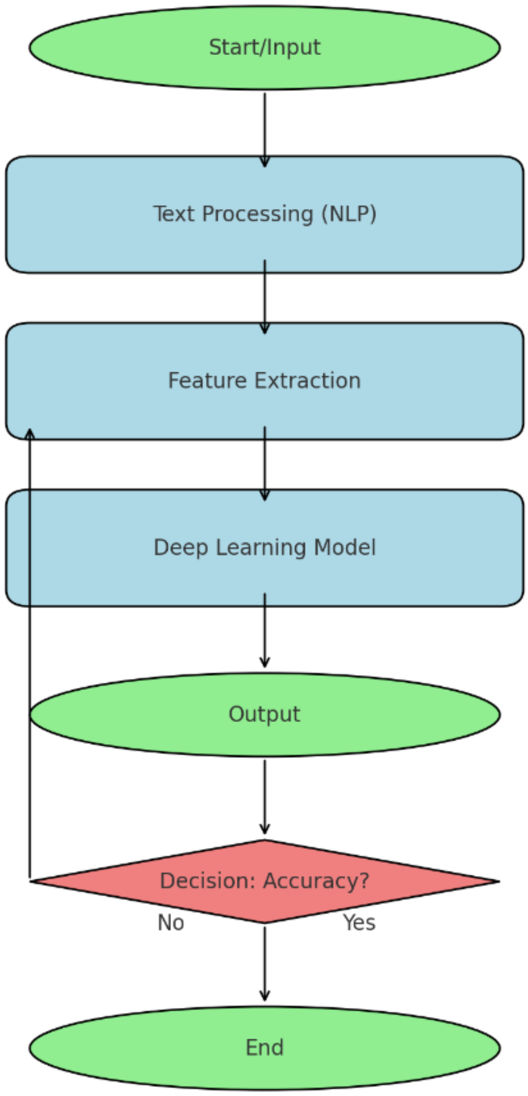

Figure 2: Workflow of the Hybrid AI Model

NLP techniques played a vital role in extracting engineering-relevant data from textual sources. For example, curing durations were linked to durability metrics, while admixture proportions were associated with flowability and strength optimisation. The processed features are summarised in Table 2, showcasing the extracted civil engineering properties, their applications, and value ranges.

Table 2: Material Properties and their Civil Engineering Applications

S.No.	Extracted Property	Source Document	Application	Value Range	Processing Technique	Reference
1	Water-to-Cement Ratio	IS 10262, ASTM C330	Strength prediction	0.35–0.55	NER	(Bai et al., 2023)
2	Aggregate Size	Research papers	Density and workability	10–20 mm	Tokenisation	(Bright Singh & Madasamy, 2022)
3	Admixture Type	Technical reports	Flowability optimisation	Plasticisers	Dependency parsing	(Sajid & Kiran, 2024)
4	Curing Conditions	IS 456	Durability assessment	7–28 days	Context extraction	(Çelikten & Erdoğan, 2022)
5	Mix Proportions	Eurocode EN 206	Material optimisation	1:2:4, 1:3:6	Text summarisation	(Zhong et al., 2023)

3.2 Deep Learning for Property Prediction

The deep learning module utilised a combination of convolutional neural networks (CNNs) and long short-term memory networks (LSTMs)(Abdar et al., 2021) . CNNs were employed to identify patterns within the numerical data, while LSTMs captured sequential dependencies, such as the effect of curing duration on compressive strength. The input features comprised both numerical data, such as mix proportions, and text-derived properties from the NLP module (Ling et al., 2024). The model was trained using a dataset of 500 samples, with an 80:20 split for training and testing. Hyperparameter tuning was conducted to optimise the model's performance.

3.3 Model Validation

The model's performance was evaluated using metrics such as R-squared, Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) (de Myttenaere et al., 2016). These metrics quantified the accuracy and reliability of the predictions for compressive strength, density, and durability. Validation against experimental results ensured the model's applicability to real-world scenarios, demonstrating its effectiveness in both predicting LWC properties and reducing the reliance on extensive physical testing.

4. Results and Discussion

The hybrid AI framework demonstrated significant improvements in predicting lightweight concrete (LWC) properties compared to traditional regression and standalone deep learning models. The integration of numerical and text-derived inputs allowed the model to process a richer dataset, enhancing its ability to capture complex relationships among variables such as water-to-cement ratio, aggregate size, and curing conditions.

For compressive strength, the hybrid AI model achieved an accuracy of 91.2%, outperforming traditional regression (78.5%) and standalone deep learning methods (85.6%), as detailed in Table 3. Similarly, durability predictions achieved 89.4% accuracy, with lower mean absolute error (MAE) and root mean squared error (RMSE) values compared to alternative approaches (Sounthararajan et al., 2020). These improvements demonstrate the hybrid model's superior ability to generalise across diverse input conditions, leveraging both structured numerical data and unstructured textual information.

Table 3: Detailed Performance Metrics for Various Prediction Models by Property

S.No.	Property	Model Type	Accuracy (%)	MAE	RMSE	R-squared
1	Compressive Strength	Traditional Regression	78.5	4.2 MPa	5.8 MPa	0.72
2	Compressive Strength	Standalone Deep Learning	85.6	3.1 MPa	4.2 MPa	0.84
3	Compressive Strength	Hybrid AI Model	91.2	2.5 MPa	3.8 MPa	0.91
4	Durability	Traditional Regression	70.4	6.5 %	8.0 %	0.65
5	Durability	Hybrid AI Model	89.4	4.1 %	5.6 %	0.88

The hybrid AI model's higher accuracy can be attributed to its dual approach of combining CNNs for processing numerical data and LSTMs for text-based features. By learning spatial and sequential patterns, the model effectively accounts for the effects of curing conditions and environmental exposure on material properties, which were often underrepresented in previous regression-based studies.

The correlation between predicted and experimental compressive strengths is illustrated in Figure 3, where the closeness of data points to the line of equality reflects the model's reliability. Minor deviations observed in the predictions are likely due to inherent variability in experimental data, such as inconsistencies in mix proportions and testing conditions. This outcome aligns with the findings of (Wei et al., 2012), who noted similar improvements when integrating diverse data types in material prediction models.

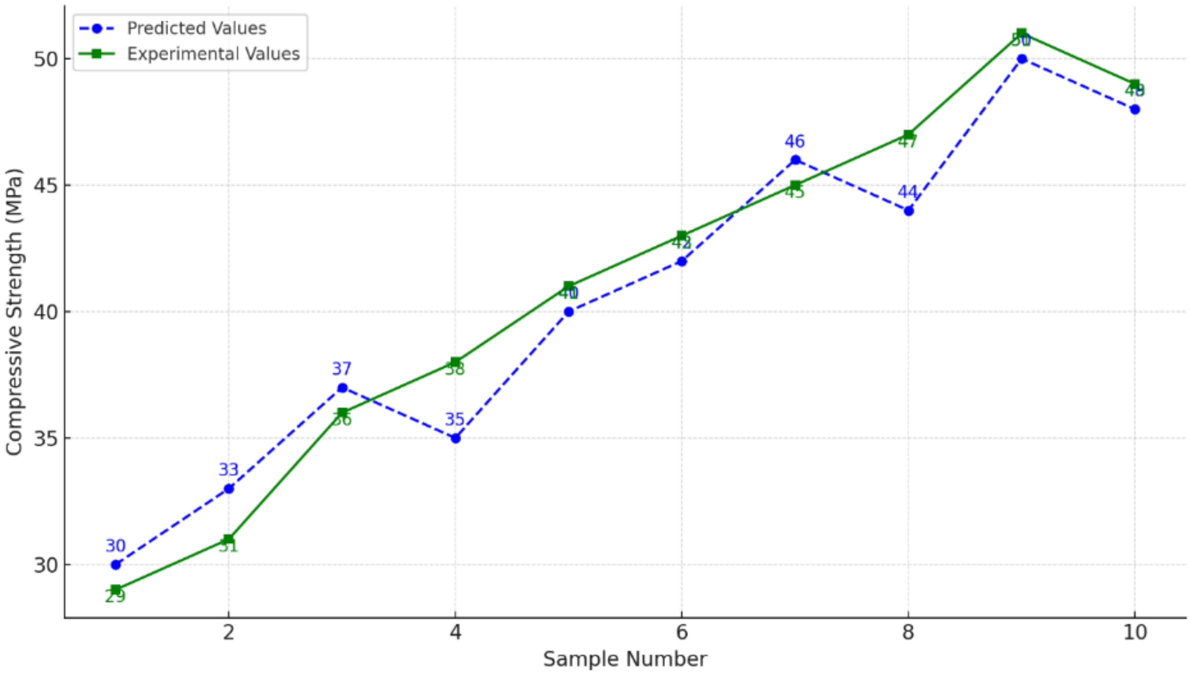

Figure 3: Predicted vs Experimental Compressive Strength

The Figure 3, shows the alignment between predicted compressive strengths and experimentally measured values, with most predictions deviating by less than ±5%. The results show that the model has ability to capture the non-linear dependencies inherent in LWC performance, reducing the need for extensive physical trials. This capability is particularly valuable for large-scale projects requiring rapid and reliable design optimisation.

The hybrid AI framework also addresses several key challenges in LWC design, as summarised in Table 4. These challenges, including high variability in mix designs and the lack of standardised AI integration in engineering codes, have traditionally hindered the adoption of data-driven approaches in civil engineering. The predictive optimisation provided by the hybrid model mitigates these issues by delivering actionable insights into mix design parameters, enabling engineers to achieve target performance metrics with minimal experimental iterations.

Table 4: Key Challenges in LWC Design and AI-Based Solutions

S.No.	Challenge	Description	AI-Based Solution
1	Material Variability	Complex dependency on mix design	Property prediction model
2	Experimental Cost	High cost of testing	AI predictions
3	Time for Optimisation	Slow iterative design processes	Predictive optimisation
4	Lack of Standards	Limited AI integration in codes	Standardisation roadmap

By streamlining the LWC design process, the hybrid model minimises experimental costs and improves the overall efficiency of engineering workflows. This advancement aligns with the vision of previous researchers, such as (Y. Yang et al., 2023), who advocated for integrating computational tools into material design practices.
The correlation between predicted and experimental durability performance is visualised in Figure 4, which shows the clustering of data points along the line of equality. This indicates a high level of agreement between predicted and observed values, underscoring the model's robustness in capturing long-term performance metrics.

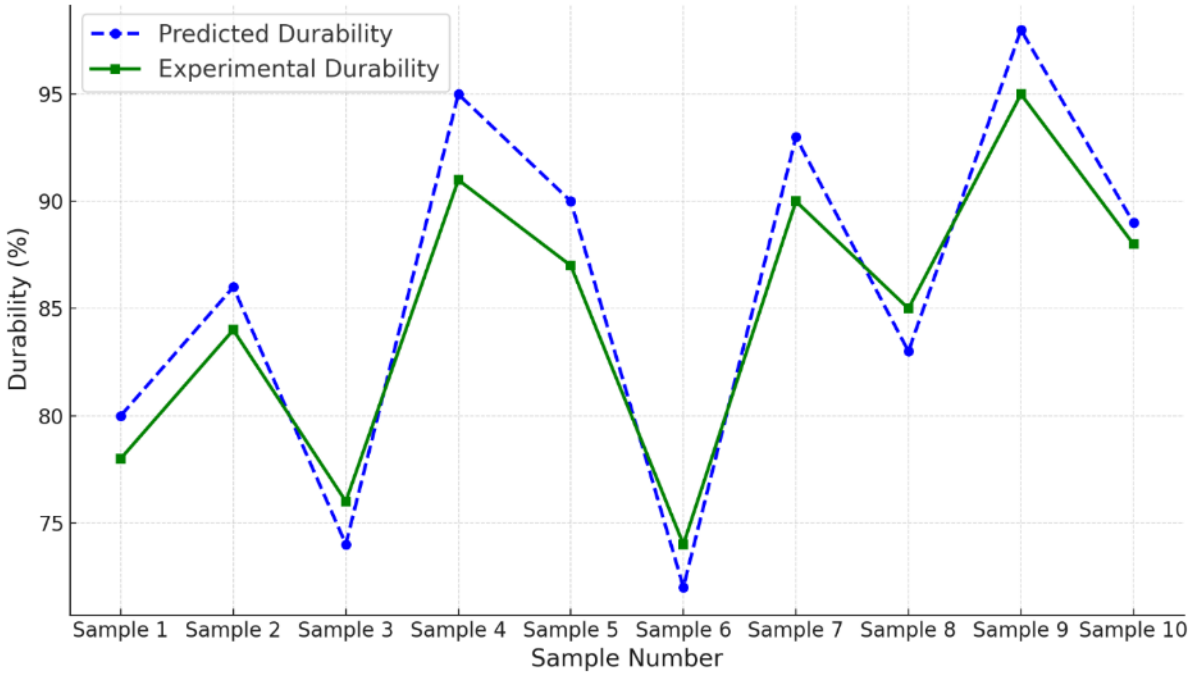

Figure 4: Correlation Between Experimental and Predicted Durability Performance

The relationship between durability predictions from the hybrid AI model and experimental results are depicted in Figure 4. This figure highlights the strong agreement between the two.

The ability of the hybrid model to integrate curing conditions and environmental exposure data into its predictions ensures that durability assessments are comprehensive and reflective of real-world scenarios. This feature distinguishes it from traditional approaches, which often lack the granularity required for accurate long-term predictions.

5. conclusions

This study demonstrates the transformative potential of a hybrid artificial intelligence (AI) framework integrating natural language processing (NLP) and deep learning for predicting lightweight concrete (LWC) properties. By combining structured numerical data with unstructured textual information, the model achieved superior accuracy, with 91.2% for compressive strength and 89.4% for durability, outperforming traditional regression and standalone deep learning approaches. The framework effectively captures complex dependencies between mix design parameters, curing conditions, and environmental factors, significantly reducing the need for extensive physical trials. This advancement not only streamlines the mix design process but also addresses key challenges in civil engineering, such as material variability and the high costs of experimental testing. The results demonstrate the potential for hybrid AI to provide actionable insights for optimising mix designs, paving the way for efficient, cost-effective, and sustainable construction practices. Future work could extend this framework to other construction materials and explore advanced AI techniques to further enhance predictive capabilities, ensuring broader adoption in modern infrastructure projects.

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