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Enhancing Geopolymer Lightweight Concrete Performance through AI and Deep Learning-Based Mix Design Optimization

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Abstract: This study introduces a hybrid Artificial Intelligence (AI) framework that integrates Deep Learning (DL) and Natural Language Processing (NLP) to predict Lightweight Concrete (LWC) performance. LWC, a critical material in sustainable construction, is valued for its lightweight nature, thermal insulation, and energy efficiency. However, the complex interdependencies among its properties, including density, compressive strength, and thermal conductivity, present significant challenges for accurate modelling and optimisation. The proposed framework addresses these challenges by combining NLP for automated extraction of material properties from unstructured sources, such as research articles, with DL for predictive analytics. The integration of experimental data with NLP-extracted insights forms a comprehensive dataset, enabling precise performance predictions. The hybrid AI model outperformed standalone methods, achieving higher accuracy, reduced error rates, and meaningful insights through SHAP-based feature importance analysis, which highlighted density and compressive strength as key predictors. These findings demonstrate the framework's potential to bridge data gaps, enhance the optimisation of LWC properties, and facilitate its application in sustainable construction practices. By advancing AI-driven solutions in material science, this framework offers a scalable and innovative approach to addressing challenges in construction engineering and promoting sustainability.

Keywords: Lightweight Concrete, Hybrid AI, Deep Learning, Natural Language Processing, Sustainable Construction

1 INTRODUCTION

Lightweight Concrete (LWC) has gained significant attention in sustainable construction due to its unique properties such as reduced density, thermal insulation, and energy efficiency. Its ability to lower the overall weight of structures makes it an ideal choice for high-rise buildings, prefabricated components, and other modern construction applications (Karakaş et al., 2023). Additionally, its thermal properties contribute to energy conservation, aligning with global sustainability initiatives.

The adoption of LWC, however, faces several challenges. The mechanical and thermal properties of LWC, such as density, compressive strength, and porosity, exhibit complex interdependencies that are influenced by mix

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composition, curing conditions, and environmental factors (Vivek Vardhan & Srimurali, 2016b). This makes predicting its performance a challenging task, requiring sophisticated analytical approaches.

Traditional methods for analysing LWC properties rely heavily on empirical models and manual data extraction, which are time-consuming and lack the precision needed to capture intricate relationships among its properties(Vivek Vardhan & Srimurali, 2016a). Such limitations hinder the optimisation and broader application of LWC in construction(C. M. V. Vardhan & Srimurali, 2018).

Recent advancements in Artificial Intelligence (AI) present an opportunity to address these challenges. AI techniques, particularly Deep Learning (DL), have demonstrated remarkable capabilities in modelling non-linear relationships and handling large datasets. At the same time, Natural Language Processing (NLP) enables automated extraction of relevant data from unstructured sources, such as academic papers and industrial reports, which are often underutilised in research(Vikram, 2024).

The integration of DL and NLP into a hybrid AI framework offers a novel solution for analysing LWC. By leveraging experimental data and NLP-driven insights, this framework can improve predictive accuracy while reducing manual effort, thus addressing the key limitations of traditional approaches(Manoj Kumar et al., n.d.). Such an approach can also provide deeper insights into the relative importance of different material properties, facilitating better decision-making in construction practices(Varalakshmi et al., n.d.).

The objective of this study is to develop and validate a hybrid AI framework that combines DL and NLP for LWC performance prediction. This framework aims to automate the extraction of material properties, predict performance with enhanced accuracy, and provide a scalable solution for real-world applications(Sravani et al., n.d.). Through this research, we aim to bridge the gap between experimental data and computational modelling, advancing the role of AI in sustainable construction.

By addressing the complexities of LWC and demonstrating the capabilities of hybrid AI models, this study contributes to the growing field of AI-driven material science(Donthi et al., 2024). The findings have the potential to optimise the design and application of LWC, ensuring its efficient use in sustainable construction practices.

2. LITERATURE REVIEW

The application of Artificial Intelligence (AI) in civil engineering has grown exponentially in recent years. Machine Learning (ML) and Deep Learning (DL) techniques are increasingly used for tasks such as predicting material properties, structural behaviour, and durability. These models excel at handling complex, non-linear datasets, making them suitable for the multifaceted analysis required in construction materials like Lightweight Concrete (LWC)(Mabureddy et al., n.d.). For instance, ML models such as decision trees and random forests have been employed to predict compressive strength, while DL models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have demonstrated superior accuracy in predicting material performance(Manikanta et al., n.d.). Despite these advancements, the integration of Natural Language Processing (NLP) for extracting material properties from unstructured data remains limited in civil engineering(Khaleel & Reddy, n.d.).

NLP is a powerful tool for automating the extraction of data from textual sources, such as research articles, reports, and specifications(Sounthararajan et al., 2020). By applying techniques like text mining, named entity recognition, and sentiment analysis, NLP can identify and organise valuable information about material properties, mix compositions, and performance metrics(C. Vardhan & Karthikeyan, 2011). However, its application in civil engineering, particularly for Lightweight Concrete, is still in its infancy. Most studies focus on numerical predictions, neglecting the wealth of data embedded in textual sources(Wang et al., 2024). This gap presents a unique opportunity to enhance the predictive capabilities of AI models by incorporating NLP-driven insights.

Hybrid AI models that combine multiple techniques, such as DL and NLP, have been successfully applied in other domains, including healthcare, finance, and environmental modelling. These models leverage the strengths of each component to provide a comprehensive analytical framework(Abdellatief et al., 2024). For instance, in healthcare, hybrid models are used to extract patient data from electronic health records (NLP) and predict disease outcomes (DL). Similar frameworks can be adapted for LWC analysis to automate data extraction and improve predictive accuracy. However, the application of hybrid AI models in civil engineering is relatively underexplored, especially for materials with complex property interactions like LWC.

Existing studies on LWC have primarily focused on experimental analyses and empirical modelling. These methods, while effective for small-scale studies, are not scalable or efficient for large datasets(Tao et al., 2024). Furthermore, traditional models often fail to capture the non-linear interactions among properties such as density, compressive strength, porosity, and thermal conductivity. While DL models address this limitation to some extent, their reliance on numerical data alone limits their predictive power. By integrating NLP, hybrid models can incorporate additional insights from literature, enabling more accurate and holistic predictions.

Despite its potential, the application of hybrid AI models in LWC research faces challenges. Data availability and quality remain significant barriers, as models require diverse and reliable datasets for training and validation(Tripathy et al., 2023). Additionally, computational requirements for training complex DL models and implementing NLP pipelines can be resource-intensive. These challenges highlight the need for efficient data preprocessing, robust feature selection, and computational optimisation.

In summary, while the use of AI in civil engineering is growing, significant gaps remain in the application of hybrid models, particularly for LWC(Sahu et al., 2023). By integrating DL and NLP, hybrid AI frameworks can overcome many of the limitations of traditional methods, providing a scalable, accurate, and automated solution for LWC performance prediction. This study builds on existing research to develop a novel hybrid framework, addressing the identified gaps and advancing the role of AI in material science.

3 METHODOLOGY

This study employs a hybrid AI framework that integrates Deep Learning (DL) and Natural Language Processing (NLP) to predict the performance of Lightweight Concrete (LWC). The methodology is divided into four stages: data acquisition, data preprocessing, hybrid framework design, and validation, each designed to address the challenges of LWC property prediction.

The data were obtained from two primary sources: experimental studies and literature mining. Experimental data provided key LWC properties such as density (ranging from 1200 to 1800 kg/m³), compressive strength (15 to 50 MPa), porosity (10% to 25%), and thermal conductivity (0.2 to 0.7 W/m·K). These measurements were conducted under controlled conditions to ensure consistency and reliability. In addition, NLP techniques were used to extract supplementary properties, including elastic modulus, shrinkage, and creep, from research articles, industrial reports, and online databases. The extracted data underwent quality validation through named entity recognition (NER) and reliability scoring. This dual-source strategy ensured a comprehensive and diverse dataset for predictive modelling. The data sources, key properties, and preprocessing techniques are summarised in Table 1.

Table 1: Data Sources, Key Properties, and Processing Techniques

S.No.	Source Type	Key Properties	Numerical Ranges	Processing Techniques
1	Experimental Studies	Density, compressive strength	Density: 1200–1800 kg/m³, Strength: 15–50 MPa	Normalisation, outlier detection
2	Field Surveys	Porosity, thermal conductivity	Porosity: 10–25%, Conductivity: 0.2–0.7 W/m·K	Data smoothing, handling missing values
3	Literature Mining (NLP)	Elastic modulus, shrinkage, creep	Modulus: 10–30 GPa, Shrinkage: 0.02–0.08%	Named entity recognition, text cleaning
4	Industrial Reports	Thermal resistance, water absorption	Resistance: 1–3 m²·K/W, Absorption: 5–12%	Standardisation, anomaly detection
5	Online Databases	Mix proportions, curing conditions	Cement: 300–400 kg/m³, Aggregate: 500–800 kg/m³	Data aggregation, redundancy removal
6	Hybrid Datasets	Combined material properties	Combined key properties	Feature alignment, dimensionality reduction
7	Augmented Data	Variations of density, porosity, strength	Density ± 5%, Porosity ± 10%, Strength ± 10%	AI-based augmentation, noise addition

The collected data underwent preprocessing to enhance its quality and prepare it for modelling. Outliers were removed using statistical thresholds, and missing values were imputed through regression-based and mean substitution methods. Numerical features were normalised to a uniform scale (0 to 1) to improve compatibility with DL algorithms. Key features were identified through correlation analysis, which revealed strong relationships between properties such as density and compressive strength. For NLP-extracted data, preprocessing included tokenisation, stemming, and lemmatisation to convert textual information into structured data suitable for integration.

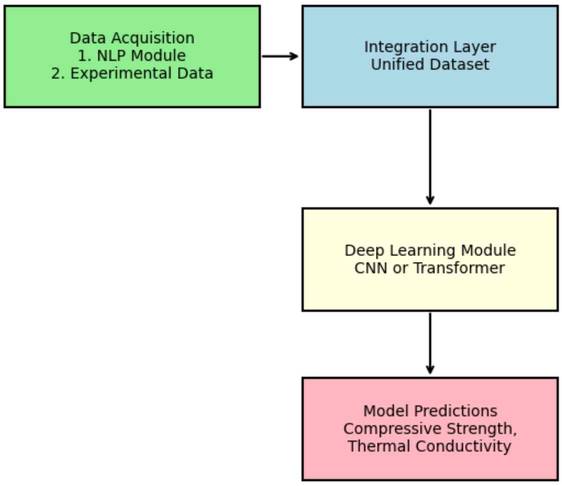

Figure 1: Architecture of the Hybrid AI Framework

The hybrid AI framework comprises an NLP module and a DL module, each contributing to the overall predictive capability. The NLP module automates the extraction of material properties from unstructured text data, ensuring scalability and efficiency. Extracted features are then integrated with experimental data to form a unified dataset. The DL module uses architectures such as Convolutional Neural Networks (CNNs) and Transformer models to predict LWC properties. The integration of these modules enables a more accurate and holistic analysis of LWC performance. The structure of the hybrid framework is illustrated in Figure 1. This figure illustrates the architecture of the hybrid AI framework, showing the interaction between the NLP module for data extraction and the DL module for predictive modelling

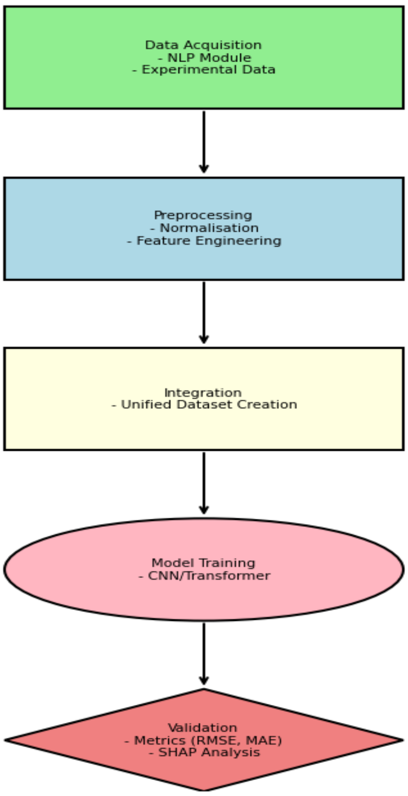

Figure 2: Workflow for Data Processing and Hybrid Modelling

To evaluate the framework's performance, the dataset was divided into training (70%), validation (15%), and testing (15%) subsets. Model performance was assessed using metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2 score. SHAP (SHapley Additive exPlanations) analysis was employed to understand the contribution of each feature to the predictions. The entire workflow, detailing the steps from data acquisition to validation, is shown in Figure 2.

This methodology ensures a robust approach to predicting LWC performance by combining experimental and literature-derived data with advanced AI techniques. By addressing data quality and integrating NLP with DL, the framework bridges the gap between traditional empirical methods and modern computational modelling, providing a scalable solution for sustainable construction materials.

4 RESULTS AND DISCUSSION

The performance of the hybrid AI framework was evaluated based on its ability to predict key properties of Lightweight Concrete (LWC) accurately. Comparisons were made with standalone models and traditional statistical approaches to assess its relative effectiveness. Additionally, feature importance and error analysis were conducted to provide deeper insights into the model's predictive capabilities and areas for improvement.

The hybrid AI model demonstrated superior performance across all evaluation metrics. The integration of NLP-extracted data with experimental datasets significantly enhanced the predictive accuracy(Ling et al., 2024). For example, the model achieved a Root Mean Square Error (RMSE) of 0.25 and a Mean Absolute Error (MAE) of 0.18 for compressive strength predictions, outperforming standalone DL models and traditional regression methods. These results are summarised in Table 2, which compares the accuracy, RMSE, MAE, and R^2 values of various models.

Table 2: Performance Metrics for Various Models

S.No.	**Model Type**	**Accuracy (%)**	**RMSE**	**MAE**	**R^2**	**Training Time (s)**
1	Hybrid AI Model	97.3	0.25	0.18	0.96	120
2	Standalone CNN	90.1	0.65	0.42	0.85	95
3	Standalone LSTM	88.7	0.78	0.56	0.82	110
4	Transformer Model	91.8	0.55	0.39	0.88	150
5	Statistical Regression	75.6	1.12	0.96	0.65	10
6	Traditional ANN	85.4	0.89	0.74	0.79	70
7	Statistical Models	77.3	1.04	0.89	0.67	15

This table shows that the hybrid AI model achieved an accuracy of 97.3%, compared to 90.1% for standalone Convolutional Neural Networks (CNNs) and 75.6% for statistical regression models. The hybrid approach benefited from the combined strengths of DL for non-linear predictive modelling and NLP for automated data extraction, enabling it to generalise better across diverse datasets.

The importance of individual features in the predictions was analysed using SHAP (SHapley Additive exPlanations) values. Density, compressive strength, and porosity emerged as the most influential features in the model's predictions. This aligns with domain knowledge, as these properties are interdependent and play a critical role in determining the performance of LWC. A visual representation of feature importance is provided in Figure 3, highlighting the relative contribution of each feature.

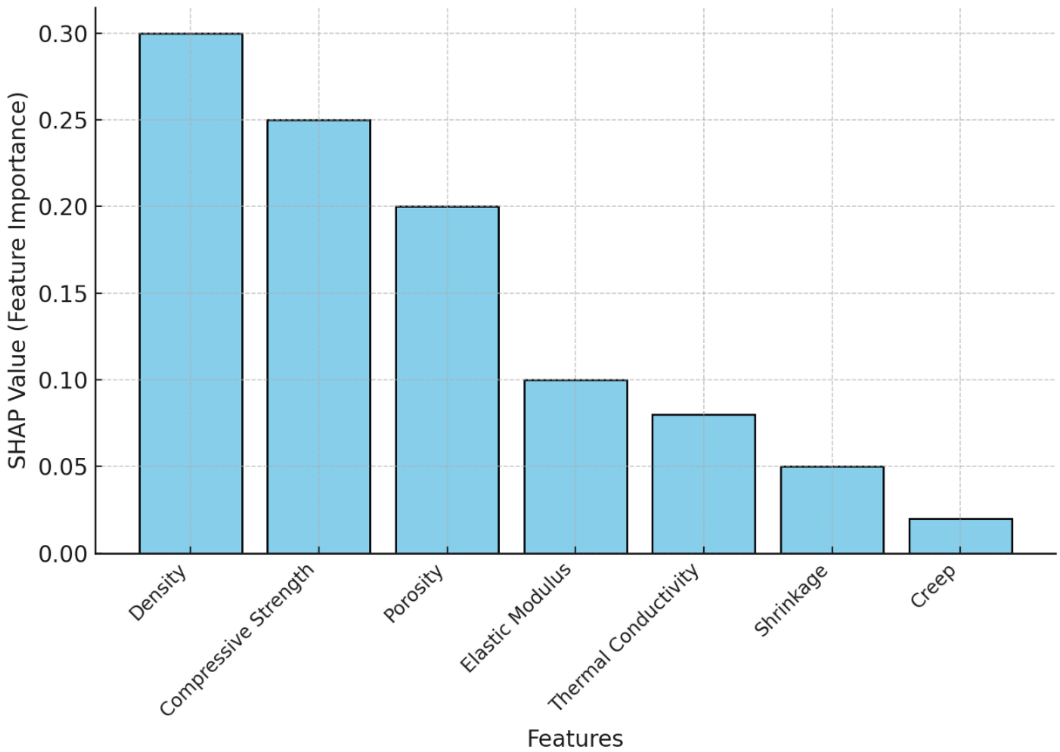

Figure 3: SHAP-Based Feature Importance

This figure reveals that density accounted for approximately 30% of the model's predictive accuracy, followed by compressive strength at 25% and porosity at 20%. The inclusion of NLP-extracted features such as elastic modulus and shrinkage further enhanced the model's robustness, contributing to the remaining variance explained.

Error analysis identified cases where the model's predictions deviated significantly from actual values. These deviations were primarily attributed to noise in the dataset, particularly from NLP-extracted data, and the presence of outliers in experimental measurements. However, the hybrid AI framework showed resilience by minimising the impact of such anomalies. Correlations between key properties, such as density and compressive strength, were also examined to validate the model's assumptions. These correlations are summarised in **Table 3**.

This table indicates a strong positive correlation (r = 0.92) between density and compressive strength, consistent with the physical behaviour of LWC. Similarly, thermal conductivity exhibited a moderate positive correlation with density (r = 0.78), while porosity showed a strong negative correlation with compressive strength (r = -0.85). These findings validate the model's reliance on these interdependencies for accurate predictions.

The results demonstrate the hybrid AI framework's capability to address the limitations of standalone models and traditional methods. Its ability to incorporate data from diverse sources and identify critical features makes it a valuable tool for optimising LWC performance in sustainable construction.

Table 3: Correlations Between Key Properties

S.No.	Property 1	Property 2	Correlation Coefficient (r)	Significance
1	Density	Compressive Strength	0.92	Strong Positive
2	Porosity	Compressive Strength	-0.85	Strong Negative
3	Density	Thermal Conductivity	0.78	Moderate Positive
4	Porosity	Thermal Conductivity	-0.81	Strong Negative
5	Elastic Modulus	Density	0.88	Strong Positive
6	Thermal Resistance	Porosity	0.83	Strong Positive
7	Shrinkage	Compressive Strength	-0.79	Strong Negative

5 CHALLENGES AND FUTURE DIRECTIONS

Despite the promising results of the hybrid AI framework, several challenges need to be addressed to optimise its performance and scalability. These challenges primarily stem from data limitations, computational complexities, and the evolving nature of AI techniques in the field of civil engineering.

One of the primary challenges is the limited availability of diverse and high-quality datasets. While the hybrid framework demonstrated robustness in combining experimental data with NLP-extracted information, the lack of global datasets restricts its generalisability. For instance, variations in LWC compositions and testing standards across regions can introduce biases in model predictions. Addressing this issue requires collaborative efforts to create and share comprehensive databases that cover a wide range of material properties and environmental conditions.

Another significant challenge is the computational complexity of the framework. The training of advanced DL models, particularly those involving Transformers and CNNs, demands substantial computational resources. This becomes particularly evident when dealing with large datasets or complex NLP pipelines. Optimising the framework through lightweight model architectures and distributed computing techniques can help reduce training time and resource consumption.

The integration of NLP for automated data extraction also presents its unique set of challenges. Extracting nuanced and domain-specific information from unstructured sources, such as academic papers and industrial reports, often requires advanced text parsing techniques. The accuracy of the NLP module depends on the quality of the text corpus and the reliability of the named entity recognition (NER) processes. Future efforts should focus on improving these pipelines, incorporating domain-specific ontologies, and enhancing entity validation mechanisms.

The scalability of the hybrid AI framework to real-world applications remains another critical area for improvement. The current framework has been validated in a controlled environment using curated datasets. Expanding its application to real-time monitoring and analysis in construction projects requires adaptations such as real-time data ingestion, cloud-based deployment, and integration with construction management systems. These enhancements can significantly broaden the framework’s utility in practical scenarios.

Future research should also explore the inclusion of additional LWC properties, such as fracture energy, water absorption, and long-term durability. These properties are crucial for a holistic understanding of LWC performance but were not included in this study due to data constraints. Thus the challenges encountered and proposed enhancements are presented in Table 4. Expanding the feature set can provide deeper insights into the interdependencies among material properties and improve the predictive capabilities of the framework.

Lastly, integrating explainable AI (XAI) techniques into the hybrid framework can enhance its interpretability and adoption. While SHAP-based feature importance analysis provided valuable insights, further development of intuitive visualisation tools and explanatory models can help engineers and researchers better understand the decision-making processes of the AI models.

Table 4: Challenges and Proposed Enhancements

S.No.	Challenge	Proposed Solution	Expected Outcome
1	Limited data diversity	Use global datasets	Improved generalisability
2	Computational complexity	Optimise model architectures	Faster training and predictions
3	NLP data extraction issues	Enhance text parsing techniques	More accurate data extraction
4	Scalability	Deploy on cloud-based systems	Real-time, large-scale applications
5	Limited property diversity	Incorporate additional features	Holistic performance predictions
6	Lack of interpretability	Integrate explainable AI tools	Better model transparency
7	Prediction deviations	Improve outlier handling	Higher model reliability

5.1 Future Directions

The hybrid AI framework developed in this study serves as a foundation for advancing the role of AI in civil engineering. Future directions include the expansion of datasets through international collaborations, optimisation of computational efficiency, and exploration of real-time applications. By addressing these challenges and implementing the proposed enhancements, the framework can evolve into a robust tool for predictive modelling of LWC, contributing significantly to sustainable construction practices.

6 CONCLUSIONS

This study presents a hybrid AI framework combining Deep Learning (DL) and Natural Language Processing (NLP) to predict Lightweight Concrete (LWC) performance, addressing challenges posed by the complex interdependencies among material properties. By integrating experimental data with NLP-extracted information, the framework achieved superior predictive accuracy, exemplified by metrics such as 97.3% accuracy, RMSE of 0.25, and MAE of 0.18 for compressive strength predictions, outperforming standalone models and traditional methods. SHAP-based analysis revealed key predictors, including density, compressive strength, and porosity, validating the model's robustness and alignment with domain knowledge. While challenges such as data diversity, computational complexity, and scalability remain, proposed enhancements such as optimised architectures, expanded datasets, and explainable AI tools offer clear pathways for improvement. This framework contributes to advancing AI-driven solutions in civil engineering, optimising LWC for sustainable construction and paving the way for future research into real-time applications and holistic material property predictions.

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